Title
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Journal
American Economic Review, 106(1)

Authors
Gorodnichenko, Yuriy
Weber, Michael

Publication Date
2016

Peer reviewed

Are Sticky Prices Costly? Evidence From The Stock Market*

Yuriy Gorodnichenko† and Michael Weber‡

This version: June 2015

Abstract

We show that after monetary policy announcements, the conditional volatility of stock market returns rises more for firms with stickier prices than for firms with more flexible prices. This differential reaction is economically large as well as strikingly robust to a broad array of checks. These results suggest that menu costs—broadly defined to include physical costs of price adjustment, informational frictions, and so on—are an important factor for nominal price rigidity at the micro level. We also show that our empirical results are qualitatively and, under plausible calibrations, quantitatively consistent with New Keynesian macroeconomic models in which firms have heterogeneous price stickiness. Because our framework is valid for a wide variety of theoretical models and frictions preventing firms from price adjustment, we provide "model-free" evidence that sticky prices are indeed costly for firms.

JEL classification: E12, E31, E44, G12, G14

Keywords: menu costs, sticky prices, asset prices, high frequency identification

*This research was conducted with restricted access to the Bureau of Labor Statistics (BLS) data. The views expressed here are those of the authors and do not necessarily reflect the views of the BLS. We thank our project coordinator at the BLS, Ryan Ogden, for help with the data, and Emi Nakamura and Jón Steinsson for making their data available to us. We thank Francesco D'Acunto, Jon Faust, Luca Fornaro (discussant), Simon Gilchrist, Robert Hall, Nir Jaimovich, Hanno Lustig, Martin Lettau, Guido Menzio, Rick Mishkin, Adair Morse, Emi Nakamura, Francisco Palomino (discussant), Ricardo Reis (discussant), Raphael Schoenle, Eric Sims, Jón Steinsson, Joe Vavra, Mike Woodford, anonymous referees, participants in the 2013 Barcelona Summer Forum, the 4^{th} Boston University/ Boston Fed Conference on Macro-Finance Linkages, Chicago, Columbia, the ECB - Bundesbank - House of Finance seminar, the 2013 ESNAS meeting, the 10^{th} German Economists abroad conference, Harvard, HEC Montreal, LSE, Munich, the NBER EFG Fall meeting 2013, the 2013 NBER SI EFG Price Dynamics working group, University of Pennsylvania, Philadelphia Fed, Santa Cruz, and especially Olivier Coibion and David Romer for valuable comments. We gratefully acknowledge financial support from the Coleman Fung Risk Management Research Center at UC Berkeley. Gorodnichenko also thanks the NSF and the Sloan Research Fellowship for financial support. Weber also thanks the University of Chicago and the Neubauer Family Foundation for financial support.

†Department of Economics, University of California at Berkeley, Berkeley, USA. email: ygorodni@econ.berkeley.edu

‡Booth School of Business, University of Chicago, Chicago, USA. email: michael.weber@chicagobooth.edu.

I Introduction

In principle, fixed costs of changing prices can be observed and measured. In practice, such costs take disparate forms in different firms, and we have no data on their magnitude. So the theory can be tested at best indirectly, at worst not at all. Alan Blinder (1991)

Are sticky prices costly? This simple question stirs an unusually heated debate in macroeconomics. Although the consensus that prices at the micro-level are fixed in the short run seems to be growing,[1] why firms have rigid prices is still unclear. A central tenet of New Keynesian macroeconomics is that firms face costs of nominal price adjustment, which can rationalize why firms may forgo an increase in profits by keeping existing prices unchanged after real or nominal shocks. However, the observed price rigidity does not necessarily entail that nominal shocks have real effects or that the inability of firms to adjust prices burdens firms. For example, Head, Liu, Menzio, and Wright (2012) present a theoretical model in which sticky prices arise endogenously even if firms are free to change prices at any time without any cost. This alternative theory has vastly different implications for business cycles and policy. How can one distinguish between these opposing motives for price stickiness?

The key insight of this paper is that in New Keynesian models, sticky prices are costly to firms, whereas in other models, they are not. Although the sources and types of menu costs are likely to vary tremendously across firms, thus making the construction of an integral measure of the cost of sticky prices extremely challenging, looking at market valuations of firms can provide a natural metric to determine whether price stickiness is indeed costly. In this paper, we exploit stock market information to explore these costs and— to the extent that firms equalize costs and benefits of nominal price adjustment— quantify menu costs. The evidence we document is consistent with the New Keynesian interpretation of price stickiness at the micro level.

Specifically, we merge confidential micro-level data underlying the producer price index (PPI) from the Bureau of Labor Statistics (BLS) with stock price data for individual firms from NYSE Trade and Quote (taq), and study how stock returns of firms with different frequencies of price adjustment respond to monetary shocks (identified as changes in futures on the fed funds rates, the main policy instrument of the Fed) in narrow time

[1] Bils and Klenow (2004), Nakamura and Steinsson (2008).

windows around press releases of the Federal Open Market Committee (FOMC). To guide our empirical analyses, we show in a basic New Keynesian model that firms with stickier prices should experience a greater increase in the volatility of returns than firms with more flexible prices after a nominal shock. Intuitively, firms with larger costs of price adjustment tolerate larger departures from the optimal reset price. Thus, the range in which the discounted present value of cash flows can fluctuate is wider. The menu cost in this theoretical exercise is generic and, hence, our framework covers a broad range of models with inflexible prices.

Consistent with this logic, we find that returns for firms with stickier prices exhibit greater volatility after monetary shocks than returns of firms with more flexible prices. The magnitudes of our estimates are broadly in line with the estimates one can obtain from a calibrated New Keynesian model with heterogeneous firms: a hypothetical monetary policy surprise of 25 basis points (bps) leads to an increase in squared returns of 8 percentage points for the firms with the stickiest prices. This sensitivity is reduced by a factor of 3 for firms with the most flexible prices in our sample. Our results are robust to a large battery of specification checks, subsample analyses, placebo tests, and alternative estimation methods.

Our work contributes to a large literature aimed at quantifying the costs of price adjustment. Zbaracki, Ritson, Levy, Dutta, and Bergen (2004) and others measure menu costs directly by keeping records of costs associated with every stage of price adjustments at the firm level (data collection, information processing, meetings, and physical costs). Anderson, Jaimovich, and Simester (2012) have access to wholesale costs and retail price changes of a large retailer. Exploiting the uniform pricing rule employed by this retailer for identification, they show that the absence of menu costs would lead to 18% more price changes. This approach sheds light on the process of adjusting prices, but generalizing these findings is difficult given the heterogeneity of adjustment costs across firms and industries. Our approach is readily applicable to any firm with publicly traded equity, independent of industry, country, or location. A second strand (e.g., Blinder (1991)) elicits information about costs and mechanisms of price adjustment from survey responses of managers. This approach is remarkably useful in documenting reasons for rigid prices, but, given the qualitative nature of survey answers, it cannot provide a magnitude of the costs associated with price adjustment. By contrast, our approach can provide a quantitative estimate of these costs. A third group of papers (e.g., Klenow and Willis (2007), Nakamura and Steinsson (2008)) integrates menu costs into fully-fledged dynamic stochastic general equilibrium (DSGE) models. Menu costs are estimated or calibrated at values that match moments of aggregate (e.g., persistence of inflation) or micro-level (e.g., frequency of price changes) data. This approach is obviously most informative if the underlying model is correctly specified. Given the striking variety of macroeconomic models in the literature and the limited ability to discriminate between models with available data, one may be concerned that the detailed structure of a given DSGE model can produce estimates that are sensitive to auxiliary assumptions necessary to make the model tractable or computable. By contrast, our approach does not have to specify a macroeconomic model, and thus our estimates are robust to alternative assumptions about the structure of the economy.[2]

Our paper is also related to the literature investigating the effect of monetary shocks on asset prices. In a seminal study, Cook and Hahn (1989) use an event-study framework to examine the effects of changes in the federal funds rate on bond rates using a daily event window. They show that changes in the federal funds target rate are associated with changes in interest rates in the same direction, with larger effects at the short end of the yield curve. Bernanke and Kuttner (2005)—also using a daily event window—focus on unexpected changes in the federal funds target rate. They find that an unexpected interest rate cut of 25 basis points leads to an increase in the CRSP value-weighted market index of about 1 percentage point. Gürkaynak, Sack, and Swanson (2005) focus on intraday event windows and find effects of similar magnitudes for the S&P500. Besides the impact on the level of returns, monetary policy surprises also lead to greater stock market volatility. For example, consistent with theoretical models predicting increased trading and volatility after important news announcements (e.g., Harris and Raviv (1993) and Varian (1989)), Bomfim (2003) finds that the conditional volatility of the S&P500 spikes after unexpected FOMC policy movements. Given that monetary policy announcements also appear to move many macroeconomic variables (see, e.g., Faust, Swanson, and Wright (2004b)), these shocks are thus a powerful source of variation in the data.

[2]Other recent contributions to this literature are Goldberg and Hellerstein (2011), Eichenbaum, Jaimovich, and Rebelo (2011), Midrigan (2011), Eichenbaum, Jaimovich, Rebelo, and Smith (2014), Bhattarai and Schoenle (2014), Vavra (2014), and Berger and Vavra (2013). See Klenow and Malin (2010) and Nakamura and Steinsson (2013) for recent reviews of this literature.

Our approach has several limitations. First, we require information on returns with frequent trades to ensure returns can be precisely calculated in narrow event windows. This constraint excludes illiquid stocks with infrequent trading. We focus on the constituents of the S&P500, which are all major US companies with high stock market capitalization.[3] Second, our methodology relies on unanticipated, presumably exogenous shocks that influence the stock market valuation of firms. A simple metric of this influence could be whether a given shock moves the aggregate stock market. Although this constraint may appear innocuous, most macroeconomic announcements other than the Fed's (e.g., the surprise component of announcements of GDP or unemployment figures by the Bureau of Economic Analysis (BEA) and BLS) fail to consistently move the stock market in the United States. Third, our approach is built on "event" analysis and therefore excludes shocks that hit the economy continuously. Forth, we follow the literature and measure a firm's stickiness as the average frequency of price adjustment. While we can rule popular alternative explanations for our findings, we have no exogenous, randomly assigned variation in frequencies and hence cannot exclude that unoberserved heterogeneity accounts for our findings (however, our placebo test does not favor this explanation). Finally, we rely on the efficiency of financial markets.[4]

The rest of the paper is structured as follows. The next section describes how we measure price stickiness at the firm level. Section III lays out a static version of a New Keynesian model with sticky prices and provides guidance for our empirical specification. This section also discusses our high-frequency identification strategy employing nominal

[3]The intraday event window restricts our universe of companies to large firms, because small stocks in the early part of our sample often experienced no trading activity for several hours even around macroeconomic news announcements, contrary to the constituents of the S&P500. Given the high volume of trades for the latter firms, news is quickly incorporated into stock prices. For example, Zebedee, Bentzen, Hansen, and Lunde (2008), among others, show that the effect of monetary policy surprises is incorporated into prices of the S&P500 within minutes. See also Neuhierl et al. (2013) for the reaction to corporate news releases more generally.

[4]Even though the information set stock market participants require may appear large (frequencies of price adjustments, relative prices, etc.), we document in Subsection *E.* of Section IV that the effects for conditional stock return volatility also hold for firm profits. Therefore, sophisticated investors can reasonably identify firms with increased volatility after monetary policy shocks, and trade on this information using option strategies such as straddles. A straddle consists of simultaneously buying a call and a put option on the same stock with the same strike price, time to maturity, and profits from increases in volatility. Analyzing the identity of traders around macroeconomic news announcements is an interesting question: private investors or rational arbitrageurs and institutional investors. Results of Erenburg, Kurov, and Lasser (2006) and Green (2004), as well as the fact that news is incorporated into prices within minutes, indicate the important role of sophisticated traders around macroeconomic news announcements.

shocks from fed funds futures and the construction of our variables and controls. Section IV presents the estimates of the sensitivity of squared returns to nominal shocks as a function of price stickiness. Section V calibrates a dynamic version of a New Keynesian model to test whether our empirical estimates can be rationalized by a reasonably calibrated model. Section VI concludes and discusses further applications of our novel methodology.

II Measuring Price Stickiness

A key ingredient of our analysis is a measure of price stickiness at the firm level. We use the confidential microdata underlying the PPI of the BLS to calculate the frequency of price adjustment for *each* firm in our sample. The PPI measures changes in selling prices from the perspective of producers, as compared to the Consumer Price Index (CPI), which looks at price changes from the consumers' perspective. The PPI tracks prices of all goods-producing industries, such as mining, manufacturing, gas, and electricity, as well as the service sector. The PPI covers about three quarters of the service sector output.

The BLS applies a three-stage procedure to determine the individual goods included in the PPI. In the first step, the BLS compiles a list of all firms filing with the Unemployment Insurance system. This information is then supplemented with additional publicly available data that are of particular importance for the service sector to refine the universe of establishments.

In the second step, individual establishments within the same industry are combined into clusters. This step ensures that prices are collected at the price-forming unit, because several establishments owned by the same company might constitute a profit-maximizing center. Price-forming units are selected for the sample based on the total value of shipments or the number of employees.

After an establishment is chosen and agrees to participate, a probability sampling technique called *disaggregation* is applied. In this final step, the individual goods and services to be included in the PPI are selected. BLS field economists combine individual items and services of a price-forming unit into categories, and assign sampling probabilities proportional to the value of shipments. These categories are then broken down further based on price-determining characteristics until unique items are identified. If identical goods are sold at different prices due to, for example, size and units of shipments, freight type, type of buyer, or color, these characteristics are also selected based on probabilistic sampling.

The BLS collects prices from about 25,000 establishments for approximately 100,000 individual items on a monthly basis. The BLS defines PPI prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month."[5] Taxes and fees collected on behalf of federal, state, or local governments are not included. Discounts, promotions, or other forms of rebates and allowances are reflected in PPI prices insofar as they reduce the revenues the producer receives. The same item is priced month after month. The BLS undertakes great efforts to adjust for quality changes and product substitutions so that only true price changes are measured.

Prices are collected via a survey that is emailed or faxed to participating establishments.[6] Nakamura and Steinsson (2008) document that the behavior of measured prices is insensitive to using alternative collection methods. Individual establishments remain in the sample for an average of seven years until a new sample is selected in the industry. This resampling occurs to account for changes in the industry structure and changing product market conditions within the industry.

We calculate the frequency of price adjustment (FPA) as the mean fraction of months with price changes during the sample period of an item. For example, if an observed price path is \$4 for two months and then \$5 for another three months, only one price change occurs during five months and hence the frequency is 1/5.[7] When calculating FPA, we exclude price changes due to sales. We identify sales using the filter employed by Nakamura and Steinsson (2008). Including sales does not affect our results in any material way because, as documented in Nakamura and Steinsson (2008), sales are rare in producer prices.

We aggregate FPA at the establishment level and further aggregate the resulting frequencies at the company level. We perform the first aggregation via internal establishment identifiers of the BLS. To perform the firm-level aggregation, we *manually*

[5] See Chapter 14, BLS Handbook of Methods, available under http://www.bls.gov/opub/hom/.

[6] The online appendix contains a sample survey.

[7] We do not consider the first observation as a price change and do not account for left censoring of price spells. Bhattarai and Schoenle (2014) verify that explicitly accounting for censoring does not change the resulting distribution of probabilities of price adjustments. Our baseline measure treats missing price values as interrupting price spells. The appendix contains results for alternative measures of the frequency of price adjustment; results are quantitatively and statistically very similar.

check whether establishments with the same or similar names are part of the same company. In addition, we search for names of subsidiaries and name changes due to, for example, mergers, acquisitions, or restructurings occurring during our sample period for all firms in our financial data set.

We discuss the fictitious case of a company, Milkwell, Inc., to illustrate aggregation to the firm level. Assume we observe product prices of items for the establishments Milkwell Advanced Circuit, Milkwell Aerospace, Milkwell Automation and Control, Milkwell Mint, and Generali Enel. In the first step, we calculate the frequency of product price adjustment at the item level and aggregate this measure at the establishment level for all of the above mentioned establishments.[8] We calculate equally-weighted frequencies (baseline) as well as frequencies weighted by values of shipments associated with items/establishments (see appendix), say, for Milkwell Aerospace. We then use publicly available information to check whether the individual establishments are part of the same company. Assume that we find that all of the above-mentioned establishments with "Milkwell" in the establishment name except for Milkwell Mint are part of Milkwell, Inc. Looking at the company structure, we also find that Milkwell has several subsidiaries: Honeymoon, Pears, and Generali Enel. Using this information, we then aggregate the establishment-level frequencies of Milkwell Advanced Circuit, Milkwell Aerospace, Milkwell Automation and Control, and Generali Enel at the company level, again calculating equally-weighted and value of shipment-weighted frequencies.

To reduce adverse effects of sampling errors, we use the full time series to construct FPA.[9] Focusing on large firms that make up the S&P500 further mitigates the potential effects of measurement errors, because these firms have many individual items in the PPI sample. In the online appendix, we provide additional evidence based on sample splits and estimation by instrumental variables to document that measurement errors do not drive our results.

Table 1 reports average frequencies of price adjustments at the firm level in Panel A, degrees of synchronization of price adjustment within firms in Panel B, as well as the

[8]Items in our data set are alpha-numeric codes in a SAS data set, and we cannot identify their specific nature.

[9]We find little variation in FPA over time at the firm level in our sample period. Allowing for time-series variation has little impact on our findings.

number of products and price spells in the PPI micro data per firm in Panels C and D.[10] Statistics are presented both for the total sample and for each industry separately.[11] The overall mean frequency of price adjustment (FPA) is 14.17%/month, implying an average duration, $-1/ln(1-FPA)$, of 6.54 months. A substantial amount of heterogeneity is present in the frequency across sectors, ranging from as low as 8.47%/month for the service sector (implying a duration of almost one year) to 26.96%/month for agriculture (implying a duration of 3.18 months). Finally, the high standard deviations highlight dramatic heterogeneity in measured price stickiness across firms even within industries. Different degrees of price stickiness of similar firms operating in the same industry can arise because of a different customer and supplier structure, heterogeneous organizational structure, or varying operational efficiencies and management philosophies.[12] The degree of synchronization in price adjustment varies across industries in a fashion similar to the frequency of price adjustment. Panels C and D show that an average firm in our sample has more than 110 unique products and 202 price spells in the micro data to measure the frequency of price adjustment.

III Framework

In this section, we outline the basic intuition for how returns and price stickiness are related in the context of a New Keynesian macroeconomic model. We will focus on one shock—monetary policy surprises—that has a number of desirable properties.[13] Although restricting the universe of shocks to only monetary policy shocks limits our analysis in terms of providing an integral measure of costs of sticky prices, it is likely to improve identification greatly and generate a better understanding of how sticky prices and stock returns are linked. This section also guides us in choosing regression specifications for the

[10] We define synchronization of price adjustment as the share of price quotes of a given firm in a given month that have a price change. For example, if a firm in a given month has five products in the BLS sample and two of the products have a price change, the synchronization rate is 2/5.

[11] The coarse definition of industries is due to confidentiality reasons and also partially explains the substantial variation of our measures of price stickiness within industry.

[12] Nakamura and Steinsson (2008) report a median frequency of price changes for producer prices between 1998 and 2005 of 10.8%, 13.3%, and 98.9% for finished producer goods, intermediate goods, and crude materials, respectively, corresponding to median implied durations of 8.7, 7, and 0.2 months.

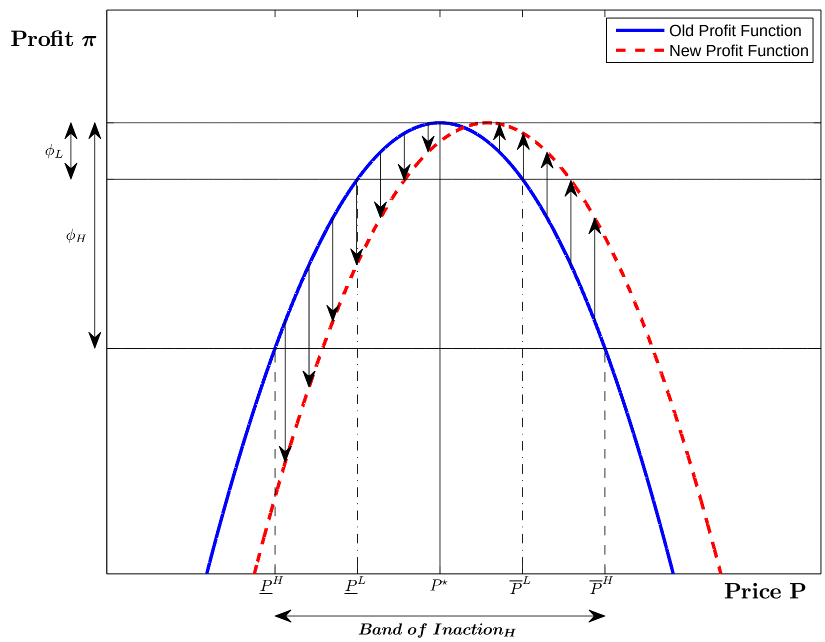
[13] Bernanke and Kuttner (2005) emphasize the importance of financial markets for the conduct of monetary policy: "The most direct and immediate effects of monetary policy actions, such as changes in the Federal funds rate, are on financial markets; by affecting asset prices and returns, policymakers try to modify economic behavior in ways that will help to achieve their ultimate objectives."

empirical part of the paper and describes how we construct variables.

A. Static model

We start with a simple, static model to highlight intuition for our subsequent theoretical and empirical analyses. Suppose that a second-order approximation to a firm's profit function is valid so that the payoff of firm i can be expressed as $\pi_i \equiv \pi(P_i, P^*) = \pi_{max} - \psi(P_i - P^*)^2$, where P^* is the optimal price given economic conditions, P_i is the current price of firm i, π_{max} is the maximum profit a firm can achieve, and ψ captures the curvature of the profit function.[14] The blue, solid line in Figure 1 shows the resulting approximation. Furthermore, assume a firm has to pay a menu cost ϕ if it wants to reset

Figure 1: Impact of a Nominal Shock on Stock Returns via a Shift in Firm's Profit Function



This figure plots profit at the firm level as a function of price. Low and high menu costs (ϕ_L and ϕ_H) translate into small and large bands of inaction within which it is optimal for a firm not to adjust prices following nominal shocks. The blue, solid line indicates the initial profit function and P^* is the initial optimal price. For example, an expansionary monetary policy shock shifts the profit function to the right, indicated by the dashed, red line. Depending on the initial position, this shift can lead either to an increase or a decrease in profits as exemplified by the arrows.

its price. This cost should be interpreted broadly as not only the cost of re-printing a menu with new prices, but also of collecting and processing information, bargaining with suppliers and customers, and so on. A firm resets its price from P_i to P^* only if the gains

[14]This expansion does not have a first-order term in $(P_i - P^*)$, because firm optimization implies that the first derivative is 0 in the neighborhood of P^*.

from doing so exceed the menu cost, that is, if $\psi(P_i - P^*)^2 > \phi$. If the menu cost is low ($\phi = \phi_L$), the range of prices consistent with inaction (non-adjustment of prices) is $(\underline{P}_L, \overline{P}_L)$. If the menu cost is high ($\phi = \phi_H$), the range of price deviations from P^* is wider $(\underline{P}_H, \overline{P}_H)$. As a result, the frequency of price adjustment is ceteris paribus lower for firms with larger menu costs. We denote the frequency of price adjustment with $\lambda \equiv \lambda(\phi)$ with $\partial\lambda/\partial\phi < 0$. We can interpret $1 - \lambda$ as the degree of price stickiness.

Without loss of generality, we can assume that prices of low-menu-cost and high-menu-cost firms are spread in $(\underline{P}_L, \overline{P}_L)$ and $(\underline{P}_H, \overline{P}_H)$ intervals, respectively, because firms are hit with idiosyncratic shocks (e.g., different timing of price adjustments as in Calvo (1983), firm-specific productivity, cost and demand shocks) or aggregate shocks we are not controlling for in our empirical exercise. Suppose there is a nominal shock that moves P^* to the right (denote this new optimal price with P^*_{new}) so that the payoff function is now described by the red, dashed line. This shift can push some firms outside their inaction bands and they will reset their prices to P^*_{new} and thus weakly increase their payoffs, (i.e., $\pi(P^*_{new}, P^*_{new}) - \pi(P_i, P^*_{new}) \geqslant \phi$). If the shock is not too large, many firms will continue to stay inside their inaction bands.

Obviously, this non-adjustment does not mean that firms have the same payoffs after the shock. Firms with negative $(P_i - P^*)$ will clearly lose (i.e., $\pi(P_i, P^*_{new}) - \pi(P_i, P^*) < 0$) as their prices become even more suboptimal. Firms with positive $(P_i - P^*_{new})$ will clearly gain (i.e., $\pi(P_i, P^*_{new}) - \pi(P_i, P^*) > 0$) as their suboptimal prices become closer to optimal. Firms with positive $(P_i - P^*)$ and negative $(P_i - P^*_{new})$ may lose or gain. In short, a nominal shock to P^* redistributes payoffs.

Note that there are losers and winners for both low-menu-cost and high-menu-cost firms. In other words, if we observe an increased payoff, we cannot infer that this increased payoff identifies a low-menu-cost firm. If we had information about $(P_i - P^*_{new})$ and/or $(P_i - P^*)$, that is, *relative* prices of firms, we could infer the size of menu costs directly from price resets. This information is unlikely to be available in a plausible empirical setting, because P^* is hardly observable.

Fortunately, there is an unambiguous prediction with respect to the variance of changes in payoffs in response to shocks. Specifically, firms with high menu costs have larger variability in payoffs than firms with low menu costs. Indeed, high-menu-cost firms can tolerate a loss of up to ϕ_H in profits, whereas low-menu-cost firms take at most a loss of ϕ_L. This observation motivates the following empirical specification:

$$(\Delta\pi_i)^2 = b_1 \times v^2 + b_2 \times v^2 \times \lambda(\phi_i) + b_3 \times \lambda(\phi_i) + error, \tag{1}$$

where $\Delta\pi_i$ is a change in payoffs (return) for firm i, v is a shock to the optimal price P^*, and $error$ absorbs movements due to other shocks. In this specification, we expect $b_1 > 0$ because a shock v results in increased volatility of payoffs. We also expect $b_2 < 0$ because the volatility increases less for firms with smaller bands of inaction and hence with more flexible prices. Furthermore, the volatility of profits should be lower for low-menu-cost firms unconditionally so that $b_3 < 0$. In the polar case of no menu costs, there is no volatility in payoffs after a nominal shock, because firms always make π_{max}.[15]

Although the static model provides intuitive insights about the relationship between payoffs and price stickiness, it is obviously not well-suited for quantitative analyses for several reasons. First, when firms decide whether to adjust their product prices, they compare the cost of price adjustment with the present value of future increases in profits associated with adjusting prices. Empirically, we measure returns that capture both current dividends/profits and changes in the valuation of firms. Because returns are necessarily forward-looking, we have to consider a dynamic model. Second, general equilibrium effects may attenuate or amplify effects of heterogeneity in price stickiness on returns. Indeed, strategic interaction between firms is often emphasized as the key channel of gradual price adjustment in response to aggregate shocks. For example, in the presence of strategic interaction and some firms with sticky prices, even flexible price firms may be reluctant to change their prices by large amounts and thus may appear to have inflexible prices (see, e.g., Haltiwanger and Waldman (1991) and Carvalho (2006)). Finally, the sensitivity of returns to macroeconomic shocks is likely to depend on the cross-sectional distribution of relative prices, which varies over time and may be difficult to characterize analytically.

[15]In a more realistic setting, strategic interaction between firms and market demand externalities can change profits for firms with flexible prices; that is, in response to shocks, the profit function can shift not only left-right, but also up-down. In this case, squared payoffs (or stock market returns) increase even for firms with perfectly flexible prices. In simulations and in the data, we find $b_1 + b_2 \approx 0$, which is consistent with left-right shifts, but it does not mean neutrality of money. The absolute and relative magnitudes of b_1 and b_2 depend on the size of shocks, degree of real rigidity, cross-sectional distribution of relative prices, and many other factors. In this basic model, we abstract from this complexity and focus on left-right shifts in the profit function to keep the intuition transparent. In addition, one can test non-neutrality of money directly using first moments; see Table 3. To be clear, we do *not* make this assumption ($b_1 + b_2 \approx 0$) in either the fully-fledged dynamic version of the model presented in Section V or in our empirical analyses.

To address these concerns and check whether the parameter estimates in our empirical analysis of Section IV are within reasonable ranges, in Section V we calibrate the dynamic multi-sector model developed in Carvalho (2006), where firms are heterogeneous in the degree of price stickiness.

B. Identification

Identification of unanticipated, presumably exogenous shocks to monetary policy is central for our analysis. In standard macroeconomic contexts (e.g., structural vector autoregressions), one may achieve identification by appealing to minimum delay restrictions whereby monetary policy is assumed to be unable to influence the economy (e.g., real GDP or unemployment rate) within a month or a quarter. However, asset prices are likely to respond to changes in monetary policy within days if not hours or minutes (see e.g. Andersen, Bollerslev, Diebold, and Vega (2003), and Rigobon and Sack (2003)).

To address this identification challenge, we employ an event-study approach in the tradition of Cook and Hahn (1989) and more recently Bernanke and Kuttner (2005). Specifically, we examine the behavior of returns and changes in the Fed's policy instrument in narrow time windows around FOMC press releases when the only relevant shock (if any) is likely due to changes in monetary policy. To isolate the unanticipated part of the announced changes of the policy rate, we use federal funds futures, which provide a high-frequency market-based measure of the anticipated path of the fed funds rate.

We calculate the surprise component of the announced change in the federal funds rate as

$$v_t = \frac{D}{D-t}(ff^0_{t+\Delta t^+} - ff^0_{t-\Delta t^-}), \tag{2}$$

where t is the time when the FOMC issues an announcement, $ff^0_{t+\Delta t^+}$ is the fed funds futures rate shortly after t, $ff^0_{t-\Delta t^-}$ is the fed funds futures rate just before t, and D is the number of days in the month.[16] The $D/(D-t)$ term adjusts for the fact that the federal funds futures settle on the average effective overnight federal funds rate.

[16]We implicitly assume in these calculations that the average effective rate within the month is equal to the federal funds target rate and that only one rate change occurs within the month. Due to changes in the policy target on unscheduled meetings, we have six observations with more than one change in a given month. Because these policy moves were not anticipated, they most likely have no major impact on our results. We nevertheless analyze intermeeting policy decisions separately in our empirical analyses. While constructing v_t, we have also implicitly assumed that a potential risk premium does not change in the $[t-\Delta t^-, t+\Delta t^+]$ window, which is consistent with results in Piazzesi and Swanson (2008).

Using this shock series, we apply the following empirical specification to assess whether price stickiness leads to differential responses of stock returns:

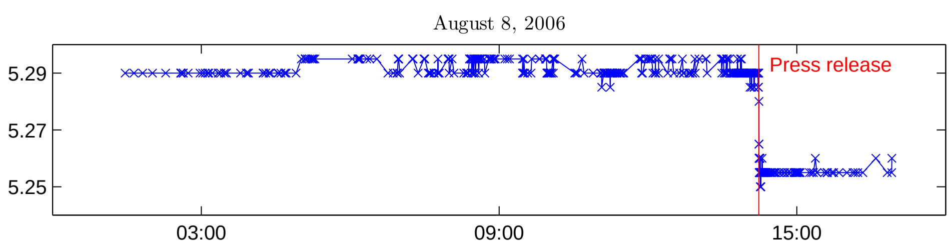
$$\begin{aligned} R_{it}^2 &= b_0 + b_1 \times v_t^2 + b_2 \times v_t^2 \times \lambda_i + b_3 \times \lambda_i \\ &\quad + FirmControls + FirmControls \times v_t^2 + error, \end{aligned} \tag{3}$$

where R_{it}^2 is the squared return of stock i in the interval $[t-\Delta t^-, t+\Delta t^+]$ around event t, v_t^2 is the squared monetary policy shock, and λ_i is the frequency of price adjustment of firm i. Below, we provide details on how high-frequency shocks and returns are constructed and we briefly discuss properties of the constructed variables. Our identification does not require immediate reaction of inflation to monetary policy shocks but can also operate through changes in current and future demand and costs that are immediately incorporated in returns through changes in the discounted value of profits.[17]

C. Data

We construct v_t using tick-by-tick data of the federal funds futures trading on the Chicago Mercantile Exchange (CME) Globex electronic trading platform (as opposed to the open-outcry market) directly from the CME. To provide an insight into the quality of the data and the adequacy of our high-frequency identification strategy, we plot the futures-based expected federal funds rate for a typical event date in Figure 2. This plot shows two general patterns in the data: high trading activity around FOMC press releases and immediate market reaction following the press release.

Figure 2: Intraday Trading in Globex Federal Funds Futures



This figure plots the tick–by–tick trades in the Globex federal funds futures for the FOMC press release on August 8, 2006, with release time at 2:14pm.

[17]Bernanke and Kuttner (2005) show for a sample period similar to ours that surprises in the federal funds rate on market excess returns operate mainly through their impact on future dividends, highlighting the importance of the cash-flow channel in explaining the effects of monetary policy shocks on *aggregate* stock market returns. Vuolteenaho (2002) shows that stock returns at the *firm* level are mainly driven by cash-flow news, contrary to the findings of Campbell (1991) and Cochrane (1992) for the *aggregate* market.

We consider "tight" and "wide" time windows around the announcement. The tight (wide) window is 30 (60) minutes and starts $\Delta t^- = 10$ (15) minutes before the press releases are issued. Panel A of Table 2 reports descriptive statistics for surprises in monetary policy for all 137 event dates between 1994 and 2009, as well as separately for turning points in monetary policy and intermeeting policy decisions.[18] Turning points (target rate changes in the direction opposite to previous changes) signal changes in the current and future stance of monetary policy and thus convey larger news (Jensen, Mercer, and Johnson (1996), Piazzesi (2005), Coibion and Gorodnichenko (2012)).

The average monetary policy shock is approximately 0. The most negative shock is more than -45 bps—about three times larger in absolute value than the most positive shock. Policy surprises on intermeeting event dates and turning points are more volatile than surprises on scheduled meetings. Lastly, the monetary policy shocks are almost perfectly correlated across the two event windows (see Figure 3 in the appendix).[19]

We sample returns for all constituents of the S&P500 for all event dates. We use the CRSP database to obtain the constituent list of the S&P500 for the respective event date and link the CRSP identifier to the ticker of the NYSE taq database (covers NYSE, Amex, and Nasdaq tick-by-tick data) via historical CUSIPs (an alphanumeric code identifying North American securities). We use the last observation before the start of the event window and the first observations after the end of the event window to calculate event returns. For the five event dates for which the press releases were issued before the start of the trading session (all intermeeting releases in the easing cycle starting in 2007; see Table 16 in the appendix), we calculate event returns—0.00,0.00,1.00measured in percentage points—using closing prices of the previous trading day and opening prices of the event day.[20]

Our sample period ranges from February 2, 1994, the first FOMC press release in

[18]Table 16 in the appendix reports event dates, time stamps of the press releases, actual target rates changes, and expected as well as unexpected changes.

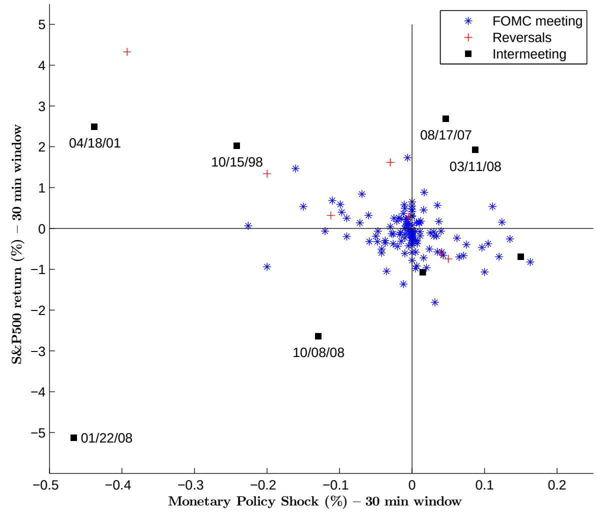
[19]Only two observations have discernible differences: August 17, 2007, and December 16, 2008. The first observation is an intermeeting event day on which the FOMC unexpectedly cut the discount rate by 50 bps at 8:15am ET just before the opening of the open-outcry futures market in Chicago. The financial press reports heavy losses for the August futures contract on that day and a very volatile market environment. The second observation, December 16, 2008, is the day on which the FOMC cut the federal funds rate to a target range between 0% and 0.25%.

[20]Intermeeting policy decisions are special in several respects, as we discuss later. Markets might therefore need additional time to fully incorporate the information contained in the FOMC press release into prices. In a robustness check, we calculate event returns using the first trade after 10:00 am on the event date. Result do not change materially.

1994, to December 16, 2009, the last announcement in 2009, for a total of 137 FOMC meetings. We exclude the rate cut of September 17, 2001—the first trading day after the terrorist attacks of September 11, 2001.[21] Panel B of Table 2 reports descriptive statistics for the percentage returns of the S&P500 for all 137 event dates between 1994 and 2009, turnings points, and intermeeting policy decisions. The average return is close to 0 with an event standard deviation of about 1%. The large absolute values of the tight (30 minute) and wide (60 minute) event returns are remarkable. Looking at the columns for intermeeting press releases and turning points, we see the most extreme observations occur on non-regular release dates. Figure 3, a scatterplot of S&P500 event returns versus monetary policy shocks, highlights this point. Specifically, this figure shows a clear negative relation between monetary policy shocks and stock returns on regular FOMC meetings and on policy reversal dates in line with Bernanke and Kuttner (2005) and Gürkaynak et al. (2005). The scatterplot, however, also documents that anything goes on intermeeting announcement days: negative (positive) monetary policy shocks induce positive and negative stock market reactions with about equal probabilities. Faust, Swanson, and Wright (2004a) argue that intermeeting policy decisions are likely to reflect new information about the state of the economy and hence the stock market reacts to this new information rather than changes in monetary policy. This logic calls for excluding

[21] Our sample starts in 1994, because our tick-by-tick stock price data are not available before 1993 and the FOMC changed the way it communicated its policy decisions. Prior to 1994, the market became aware of changes in the federal funds target rate through the size and the type of open market operations of the New York Fed's trading desk. Moreover, most of the changes in the federal funds target rate took place on non-meeting days. With the first meeting in 1994, the FOMC started to communicate its decision by issuing press releases after every meeting and policy decision. Therefore, the start of our sample eliminates almost all timing ambiguity (besides the nine intermeeting policy decisions). The increased transparency and predictability makes the use of our intraday identification scheme more appealing because our identification assumptions are more likely to hold.

Figure 3: Return of the S&P500 versus Monetary Policy Shocks (tight window)



This figure is a scatterplot of the percentage returns on the S&P500 versus the federal funds futures-based measure of monetary policy shocks calculated according to equation 2 for the tight (30min) event window. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. We distinguish between regular FOMC meetings, turning points in monetary policy, and intermeeting press releases.

intermeeting announcements.[22]

Firms are heterogeneous in many dimensions. Ehrmann and Fratzscher (2004) and Ippolito, Ozdagli, and Perez (2013), among others, show that firms with low cash flows, small firms, firms with low credit ratings, high price-earnings multiples, and Tobin's q show a higher sensitivity to monetary policy shocks, which is in line with bank lending, balance sheet, and interest rate channels of monetary policy. To rule out that this heterogeneity drives our results, we control for an extended set of variables at the firm and industry level. For example, we construct measures of firm size, volatility, cyclical properties of demand, market power, cost structure, financial dependence, access to

[22] Romer and Romer (2000) document that the inflation forecasts of the Fed's staff beat commercial forecasts, which is consistent with the Fed having an informational advantage over professional forecasters, and thus opens a possibility that our measured surprises in the fed funds rate can capture both policy surprises and the Fed's revelation of information about the state of the economy. On the other hand, Coibion and Gorodnichenko (2012) document (see their Table 6) that, at least over the horizons of a few quarters, financial markets are as good at predicting movements in the fed funds rates as the Fed's staff, and hence, quantitatively, the revelation component is probably small. In addition, Faust et al. (2004a) argue that FOMC announcements do not contain superior information about the state of the economy, because professional forecasters do not systematically change their forecasts for a wide range of macroeconomic variables following FOMC press releases, and these forecasts are efficient given the announcement. Finally, although the revelation component can make the mapping of empirical results to a theoretical model less straightforward, it does not invalidate our empirical analysis, because we only need an unanticipated shock that moves optimal reset prices and therefore returns. The nature of this shock is not material.

financial markets, and so on. We use data from a variety of sources, such as the Standard and Poor's Compustat database, publications of the U.S. Census Bureau, and previous studies. The appendix contains detailed information on how we measure these variables.

IV Empirical Results

A. Aggregate Market Volatility

We first document the effects of monetary policy shocks on the return of the aggregate market to ensure these shocks are a meaningful source of variation. Table 3 reports results from regressing returns of the S&P500 on monetary policy surprises, as well as squared index returns on squared policy shocks for our tight event window (30 minute). Column (1) shows that a higher than expected federal funds target rate leads to a drop in stocks prices. This effect—contrary to findings in the previous literature—is not statistically significant. Restricting our sample period to 1994-2004 (or 1994-2007), we can replicate the results of Bernanke and Kuttner (2005), Gürkaynak et al. (2005), and others: a 25 bps unexpected cut in interest rates leads to an increase of the S&P500 by more than 1.3%. In column (3), we find a highly statistically significant impact of squared policy shocks on squared index returns. Conditioning on different types of meetings shows that turning points in monetary are the major driver of the overall effect. Widening the event window mainly adds noise, increasing standard errors and lowering R^2s, but does not qualitatively alter the results.[23] In summary, monetary policy surprises are valid shocks for our analysis.

B. Baseline

Panel A in Table 4 presents results for the baseline specification (3), where we regress squared event returns at the firm level on the squared policy surprise, the frequencies of price adjustments, and their interactions. We cluster standard errors at the event level and report them in parentheses, but statistical inference is similar if we employ Driscoll and Kraay (1998) standard errors, which account for correlation of error terms across time and firms.

Column (1) of Panel A shows that squared surprises have a large positive impact

[23] Appendix Table 2 in the online appendix contains results both for the 30-minute event window in columns (1) to (6) as well as the 60-minute event window in columns (7) to (12).

on squared stocks returns. The point estimate is economically large and statistically significant at the 1% level: a hypothetical policy surprise of 25 bps leads to an increase in squared returns of roughly 8 percentage points (=$0.25^2 \times 128.50$) which corresponds to a return of 2.83 percentage points.[24] The estimated coefficient on the interaction of the frequency of price adjustment and the squared shock indicates that this effect is lower for firms with more flexible prices. For the firms with the most flexible prices in our sample (which have a probability of price adjustment of roughly 0.5 per month), the impact of squared monetary policy shocks is reduced by a factor of 3, that is, $(\beta_1 - 0.5 \times \beta_3)/\beta_1 \approx 1/3$. Importantly, this sensitivity is broadly in line with the estimates we obtain for simulated data from a calibrated New Keynesian model (see Section V).

The differential response of conditional volatility for sticky and flexible price firms is a very robust result. Controlling for outliers (column (2)),[25] adding firm fixed effects (columns (3) and (4)), adding firm and event (time) fixed effects (columns (5) and (6)), or looking at a 60-minute event window (columns (7) and (8)) does not materially change point estimates and statistical significance for the interaction term between squared policy surprises and the frequency of price adjustment. Increasing the observation period to a daily event window (columns (9) and (10)) adds a considerable amount of noise, reducing explanatory power and increasing standard errors. Point estimates are no longer statistically significant, but they remain economically large, and relative magnitudes are effectively unchanged. This pattern is consistent with Bernanke and Kuttner (2005) and Gürkaynak et al. (2005), documenting that for the aggregate market, R^2s are reduced by a factor of 3 and standard errors increase substantially as the event window increases to the daily frequency.[26]

We use only two data ticks in the baseline measurement of stock returns; we find similar results for returns weighted by trade volume in time windows before and after our events (Panel B, columns (1) and (2)). As is conventional in finance, our baseline

[24] We use the square of returns in percent as the dependent variable in our regressions.

[25] We use a standard approach of identifying outliers by jackknife as described in Belsley et al. (1980) and Bollen and Jackman (1990). Our results do not change materially for reasonable variation in the threshold identifying observations as outliers; see Appendix Table 9.

[26] Although additional macro announcements or stock-market-relevant news can explain the effects for the aggregate market, many more stock-price-relevant news can be observed for individual stocks, such as earning announcements, analyst reports, management decisions, and so on, rationalizing the large increase in standard errors. Rigobon and Sack (2004) and Gürkaynak and Wright (2013) also highlight that intraday event windows are more well suited from an econometric point of view, because daily event windows might give rise to biased estimates.

specification uses squared returns and squared policy surprises, but using this measure of volatility can amplify adverse effects of extreme observations. In addition to identifying and excluding outliers and influential observations by jackknife, we also address this potential concern by using a specification with absolute values of returns $|R_{it}|$ and policy shocks $|v_t|$, which gives a lower weight to potential outliers. The results do not change qualitatively when we use absolute returns and policy shocks (columns (3) and (4) of Panel B) instead of squared returns and squared shocks.

One may be concerned that the heterogeneity in volatility across firms is largely driven by market movements or exposure to movements of other risk factors rather than forces specific to the price stickiness of particular firms. To address this concern, we consider squared market-adjusted returns (i.e., $(R_{it} - R_t^{SP})^2$), squared CAPM-adjusted returns (i.e., $(R_{it} - \beta_i R_t^{SP})^2$), and squared Fama-French-adjusted returns ($(R_{it} - \beta_{iFF} R_t^{FF})^2$) where β_i and β_{iFF} are time-series factor loadings of the excess returns of firm i on the market excess returns and the three Fama-French factors. All three adjustments (Panel B: columns (5) and (6), columns (7) and (8), and columns (9) and (10)) take out a lot of common variation, reducing both explanatory power and point estimates somewhat but leaving statistical significance and relative magnitudes unchanged or even increasing them slightly. This reduced but significant sensitivity of market-adjusted returns is consistent with Weber (2015). He documents that β is a function of price stickiness. As a result, the increased volatility of stock returns for firms with stickier prices in response to nominal shocks is partially realized via increased riskiness of these stocks. Because we are interested in the total effect of price stickiness on conditional volatility of stock returns, we continue to use unadjusted returns as the baseline.[27]

The sensitivity of conditional volatility to monetary policy shocks may vary across types of events. For example, Gürkaynak et al. (2005) and others show that monetary policy announcements about changes in the path/direction of future policy are more powerful in moving markets. Panel C of Table 4 contains results for different event types. We restrict our sample in columns (3) and (4) to observations before 2007 to control for the impact of the Great Recession and the zero lower bound. The effect of price flexibility increases both statistically and economically in the restricted sample. In the next two columns, we follow Bernanke and Kuttner (2005) and restrict the sample to only episodes

[27] The online appendix contains additional results for adjusted returns.

in which the FOMC changed the policy interest rate. Although this restriction reduces our sample size by more than 50%, it has no impact on estimated coefficients. Some of the monetary policy shocks are relatively small. To ensure these observations do not drive the large effects of price rigidity, we restrict our sample to events with shocks larger than 0.05 in absolute value in columns (7) and (8). Both for the full and the no-outliers samples, statistical and economic significance remains stable or even slightly increases. When we constrain the sample to turning points in policy, the coefficient on the interaction term between the probability of price adjustment and squared policy shocks increases by a factor of three. The effect of policy shocks is somewhat larger for intermeeting releases, as shown in the last column.

C. Additional controls and analysis of subsamples

Although the simple framework in Section III considers only heterogeneity in menu costs as a source of variation in the frequency of price adjustment, FPA depends on a number of factors that determine benefits and costs of price adjustment, such as the curvature of the profit function and the volatility shocks. In Table 5, we add a wide range of controls to disentangle the effect of price stickiness from potentially confounding firm- and industry-level factors.

In the first column, we repeat the baseline regression, excluding outliers. In the first set of controls, we focus on measures of market power and profitability. For example, in column (2), we include the squared shock interacted with the price cost margin (*pcm*) as an additional regressor. Although firms with larger *pcm* appear to have volatility more sensitive to monetary policy shocks, including *pcm* does not alter our conclusions about the sensitivity across firms with different frequencies of price adjustment. Likewise, controlling directly for market power with industry concentration (the share of sales by the four largest firms, $4F - conc\ ratio$, column (3)) does not change our main result. We also find that our results for b_2 in equation (3) do not alter when we control for the book-to-market ratio (column (4)) or firm size (column (5)).[28]

The differential sensitivity of volatility across sticky- and flexible-price firms may arise from differences in the volatility of demand for sticky- and flexible-price firms. For

[28]Note that the coefficient on the squared policy surprise now turns negative. This coefficient, however, can no longer be as easily interpreted as before in the presence of additional control variables. If we report results evaluating additional controls at their mean level, coefficients are similar in size to our benchmark estimation.

example, all firms could face identical menu costs, but firms that are hit more frequently by idiosyncratic shocks have a higher FPA and hence may be closer to their optimal reset prices, which in turn suggests they could have a lower sensitivity to nominal shocks. To disentangle this potentially confounding effect, we explicitly control for the volatility of sales (standard deviation of sales growth rates, *std sale*,[29] column (6)) and for durability of output (columns (7) and (8)) using the classifications of Gomes, Kogan, and Yogo (2009) and Bils, Klenow, and Malin (2012), respectively. The latter control is important, because demand for durable goods is particularly volatile over the business cycle, and consumers can easily shift the timing of their purchases, thus making price sensitivity especially high. Even with these additional regressors, we find the estimated differential sensitivity of volatility across sticky- and flexible-price firms is largely unchanged.

Some heterogeneity of stickiness in product prices may reflect differences in the stickiness of input prices. For example, labor costs are often found to be relatively inflexible because of rigid wages. When we control for input price stickiness proxied by the share of labor expenses in sales (column 9) and by the frequency of wage adjustment at the industry level from Barattieri, Basu, and Gottschalk (2014) (column 10), we find that firms with a larger share of labor cost have greater sensitivity to monetary policy shocks, but these additional controls do not affect our estimates of how stickiness of product prices influences conditional volatility of returns. In columns (11) to (22), we additionally control for the receivables minus payables-to-sales ratio ($RecPay2Y$) to control for the impact of short-term financing, investment-to-sales ratio ($I2Y$) to control for investment opportunities, the depreciation-to-assets ratio ($D2A$) as a measure of capital intensity, Engel curve slopes ($engel$) to control for differences in income elasticities, the rate of synchronization in price adjustments within a firm ($sync$), the number of products at the firm level ($\#prod$), the S&P long-term issuer rating (Rat), the Kaplan - Zingales index (KZ) to investigate the impact of financial constraints, financial leverage (lev) to take into account its effect on risk and returns, fixed costs to sales ($FC2Y$) because a higher ratio might decrease the flexibility to react to monetary policy shocks, as well as the share of sales abroad to overall sales ($export$) because companies with a larger share might be less responsive to U.S. monetary policy. Overall, none of the controls—either individually

[29]We use the standard deviation of annual sales growth at the quarterly frequency to control for seasonality in sales. Ideally, we would want to have higher frequency data to construct this variable, but publicly available sources only contain sales at the quarterly frequency.

or jointly—attenuates the effect of price stickiness, which is highly statistically and economically significant.[30]

In Table 6, we run our baseline regression at the industry level to further mitigate concerns about omitted factors and control for generally unobserved industry heterogeneity. In this exercise, we have typically many fewer firms, and thus estimates have higher sampling uncertainty. Despite large reductions in sample sizes, for four out of the six industries we find a statistically significant negative coefficient on the interaction term between the frequency of price adjustment and squared monetary policy surprises. For the finance industry, this coefficient is not statistically significant. For the service sector, the estimate for the full sample is positive and significant, but a handful of outliers drive this result. Once these outliers are removed, the point estimate becomes much smaller and statistically insignificantly different from zero. One may be concerned that our results might be driven by sectors sensitive to interest rate movements, such as sectors producing durable goods. In columns (10) and (11), we present results for the sample of firms in sectors producing non-durables as defined by Bils et al. (2012). Estimates for this sample are similar to the baseline, and hence increased conditional volatility of returns for sticky-price firms applies broadly across sectors.[31]

An alternative possibility that could drive our results is a general return sensitivity to monetary policy surprises independent of price stickiness. For example, stocks of some firms may be more volatile because these firms have a larger exposure to interest rate risk, which raises their stock volatility in response to monetary shocks. To rule out this alternative explanation, we add another control: the return sensitivity to monetary policy shocks.[32] Specifically, we first estimate the sensitivity (β_{v_t}) by regressing firm-level event returns on monetary policy shocks in our narrow event window. Then we add the return sensitivity interacted with the squared monetary policy surprise in various specifications as an additional control variable in our baseline regression. Table 7 shows that a higher

[30]To explore whether unobserved selection might bias our point estimates, we follow Oster (2013) and compare points estimates and movement in R^2s between our baseline estimate and the model with the full set of controls. The correction term is equal to -186 and it is precisely estimated. This correction indicates that our point estimates might be conservative.

[31]In addition to using firm or industry fixed effects, we estimated specifications in which we define FPA as deviations from industry means to rule out the concern that industry characteristics orthogonal to costs of price adjustment might be driving parts of the effect of price stickiness on conditional volatility. We found that this alternative approach yields results similar to the baseline.

[32]We thank David Romer for suggesting this test.

squared return sensitivity to monetary policy surprises indeed leads to an increase in event return volatilities, but this additional control has a negligible effect on the interaction term of our measure of price stickiness and squared monetary policy shocks.

Basic New Keynesian theory predicts the sensitivity of conditional volatility should be larger for firms with stickier prices, because these firms can deviate more from optimal prices. To test this prediction, we split the sample into two halves based on firms' frequency of price adjustment, FPA, and estimate specification (3) for each half separately. As theory suggests, the coefficient on the interaction term between price stickiness and policy shock is larger for the set of sticky-price firms (columns (1) and (2) compared to columns (3) and (4) of Table 8). To further explore this prediction, we estimate a specification that is non-linear in the frequency of price adjustment, FPA:

$$\begin{aligned} R_{it}^2 &= b_0 + b_1 \times v_t^2 + b_2 \times v_t^2 \times \lambda_i + b_3 \times v_t^2 \times \lambda_i^2 \\ &\quad + b_4 \times \lambda_i + b_5 \times \lambda_i^2 + error. \end{aligned} \tag{4}$$

Columns (5) and (6) in Table 8 show the point estimates of the slopes are consistent with increased sensitivity of stock returns for firms with the stickiest prices (i.e., b_2 is negative and b_3 is positive), but standard errors are too large to have conclusive results.

Finally, we examine if some parts of the FPA distribution drive the sensitivity of the conditional volatility of stock returns to monetary policy shocks. Specifically, we split firms by quintiles of the frequency of price adjustment and estimate the following regression for each quintile separately:

$$R_{it}^2 = b_0 + b_1 \times v_t^2 + error. \tag{5}$$

Columns (7) through (11) show the estimated sensitivity is largest for firms with the stickiest price, and declines monotonically in the frequency of price adjustment. The estimated sensitivity in the top quintile (most flexible prices) is about half of the estimated sensitivity for the bottom quintile (stickiest prices), which is in line with the decline in the sensitivity we obtain in the baseline, parametric specification (3). Thus, our baseline findings apply broadly across firms with different frequencies of price adjustment.

D. Relative Volatility and Placebo Test

Empirically, we find a large and robust effect of the frequency of price adjustment on the association between monetary policy shocks and conditional volatility of stock returns. The effect survives a series of robustness checks aimed at ruling out alternative explanations and factors determining costs and benefits of price adjustment. Ideally, we would like to identify and exploit a source of exogenous variation in the frequency of price adjustment to reinforce conclusions from these tests. In the lack thereof, we perform two additional economically motivated robustness checks to further examine potentially confounding unobserved firm heterogeneity: one in which price stickiness should matter and one in which we do not expect to find an effect of price stickiness.

The first check is built on the following idea. Suppose that there is some unobserved firm characteristic that makes sticky-price firms have unconditionally higher volatility than flexible-price firms. In this case, we may find a high sensitivity of sticky-price firms simply because these firms tend to have high volatility on average. However, if this phenomenon drives the previously documented effects, we should find no effects of price stickiness once we scale the event volatilities by their unconditional volatilities which summarize the effect of this characteristic. To implement this test, we pick a pseudo event window in the middle of two adjacent event dates t and $t-1$ (date $\tau = t-1/2$) and calculate a pseudo event volatility $(1 + R_{i\tau})^2$ in a 30-minute window bracketing 2:15PM on date τ. We then scale the event volatilities of the following event date with these volatilities, $(1 + R_{it})^2/(1 + R_{i\tau})^2$, and run our baseline regression with $(1 + R_{it})^2/(1 + R_{i\tau})^2$ as the dependent variable.

Column (1) in Panel A of Table 9 shows this explanation cannot account for our result that flexible-price firms have lower conditional volatilities than sticky-price firms. Monetary policy surprises increase event volatility compared to non-event dates. This conditional increase is completely offset for the most flexible firms, with both coefficients being highly statistically significant. Controlling for outliers in column (2), firm fixed effects, event fixed effects, or both in columns (3) to (8) does not change this conclusion.

The second check on whether unobserved heterogeneity can drive our results is to run our baseline regression directly on the pseudo event volatilities $(1 + R_{i\tau})^2$. We perform this test in Panel B of Table 9: all coefficients are economically small, none of them is statistically significant, and once we exclude outliers, the coefficient on the interaction term between the monetary policy surprise and the frequency of price adjustment changes sign.

Both tests confirm our baseline findings and help alleviate concerns that our findings might be spurious. However, what determines heterogeneity in the frequency of price adjustment across similar firms within industries is still an open question, as is the identification of a credible source of exogenous variation in FPA.

E. Fundamentals

The large differential effects of price stickiness on the volatility of returns suggest that firms with inflexible prices should experience an increased volatility of profits relative to firms with flexible prices. Detecting this response in fundamentals may be difficult, because information on firm profits is only available at the quarterly frequency. To match this much lower frequency, we add shocks v_t in a given quarter and treat this sum as the unanticipated shock. Denote this shock with $\tilde{v}_t$. We also construct the following measure of change in profitability between the previous four quarters and quarters running from $t+H$ to $t+H+3$:

$$\Delta\pi_{it,H} = \frac{\frac{1}{4}\sum_{s=t+H}^{t+H+3} OI_{is} - \frac{1}{4}\sum_{s=t-4}^{t-1} OI_{is}}{TA_{it-1}} \times 100, \tag{6}$$

where OI is the quarterly operating income before depreciation, TA is total assets, and H can be interpreted as the horizon of the response. We use four quarters before and after the shock to address seasonality of profits. Using this measure of profitability, we estimate the following modification of our baseline specification:

$$(\Delta\pi_{it,H})^2 = b_0 + b_1 \times \Delta\tilde{v}_t^2 + b_2 \times \tilde{v}_t^2 \times \lambda_i + b_3 \times \lambda_i + error. \tag{7}$$

We find (Panel A, Table 10) that flexible-price firms have a statistically lower volatility in operating income than sticky-price firms ($b_2 < 0$). This effect is increasing up to $H =$ six quarters ahead and then this difference becomes statistically insignificant and gradually converges to zero. Firms with stickier prices (smaller FPA) tend to have larger volatilities of profits.[33]

Although these dynamics of profits are consistent with the logic of New Keynesian models, one may gain further insight into sources of increased volatility of profits by examining how volatility of capital expenditures responds to monetary shocks. Specifically, one may be concerned that firms that adjust prices less frequently, also adjust everything else (e.g., employment, investment) weakly and hence experience increased volatility of profits. Using the same aggregation procedure and normalization as we

[33]Interestingly, the estimate of b_1 is statistically positive only at $H = 0$ and turns statistically negative after $H = 5$.

employed for profits, we utilize Compustat data to calculate investment rates for each firm and then use econometric specification (7) with squared investment rates as the dependent variable to investigate if such concerns are founded.[34] We find (Panel B, Table 10) that, similar to profits, capital expenditures are more volatile for firms with stickier prices in response to monetary shocks. Although we do not have data to study other margins of adjustment, the behavior of capital expenditures is inconsistent with the view that sticky-price firms are also sticky along other margins.

V Dynamic General Equilibrium Model

Our regression results suggest price stickiness is potentially costly for firms. Although we cannot completely rule out potentially confounding factors in the data, we can abstract from these factors in a theoretical model and assess whether the estimated sensitivity of stock return volatility is quantitatively rationalizable when the only source of heterogeneity across firms is the degree of price stickiness. To this end, we use the Calvo (1983) model, the workhorse framework for monetary analyses, and enrich it with heterogeneous frequency of price adjustment as in Carvalho (2006). Models with sufficiently many add-on features interacted with alternative sources of firm heterogeneity may be able to capture the patterns we observe in the data, but a key advantage of our approach is that we use a standard, "barebones" model and thereby impose strong discipline on the exercise. In addition, a model in the spirit of Carvalho (2006) allows simple aggregation of heterogeneous firms and a fast and precise solution for and simulation of non-linear dynamics, which is central for modeling risk and volatility.

In the interest of space, we only verbally discuss the model, and focus on key equations.[35] In this model, a representative household lives forever. The instantaneous utility of the household depends on consumption and labor supply. The intertemporal elasticity of substitution for consumption is σ. Labor supply is firm-specific. For each firm, the elasticity of labor supply is η. The household's discount factor is β. Households have a love for variety and have a CES Dixit-Stiglitz aggregator with the elasticity of substitution θ.

[34] We use capital expenditure data from the quarterly Compustat file (item *capxy*). *capxy* represents year-to-date capital expenditure. We transform the variable so that it represents quarterly capital expenditure.

[35] The appendix contains a more detailed description of the model.

Firms set prices as in Calvo (1983). The economy contains k sectors, with each sector populated by a continuum of firms. Each sector is characterized by a fixed λ_k, the probability of any firm in industry k adjusting its price in a given period.[36] The share of firms in industry k in the total number of firms in the economy is given by the density function $f(k)$. Firms are monopolistic competitors and the elasticity of substitution θ is the same for all firms, both within and across industries. Although this assumption is clearly unrealistic, it greatly simplifies the algebra and keeps the model tractable. The production function for output Y is linear in labor N, which is the only input. The optimization problem of firm j in industry k is then to pick a reset price X_{jkt}:

$$\max \mathbb{E}_t \quad \sum_{s=0}^{\infty} Q_{t,t+s}(1-\lambda_k)^s [X_{jkt}Y_{jkt+s} - W_{jkt+s}N_{jkt+s}], \tag{8}$$

subject to its demand function and production technology, where variables without subscripts k and j indicate aggregate variables, W is wages (taken as given by firms), and Q is the stochastic discount factor. The household's intratemporal elasticity between labor and consumption determines wages. The central bank follows an interest rate rule.

After substituting in optimal reset prices and firm-specific demand and wages, the value of the firm V with price P_{jkt} is given by:

$$V(P_{jkt}) \quad = \quad \mathbb{E}_t \left\{ Y_t^{\sigma} P_t \left[\Delta_{kt}^{(1)} \left(\frac{P_{jkt}}{P_t} \right)^{1-\theta} - \Delta_{kt}^{(2)} \left(\frac{P_{jkt}}{P_t} \right)^{-\theta(1+1/\eta)} + \Upsilon_{kt}^{(1)} - \Upsilon_{kt}^{(2)} \right] \right\}, \tag{9}$$

where $\Upsilon_{kt}^{(1)}$, $\Delta_{kt}^{(1)}$, $\Upsilon_{kt}^{(2)}$, and $\Delta_{kt}^{(2)}$ follow simple recursions and are not indexed by j, which allows particularly easy solution and simulation of this non-linear model.

We calibrate the model at quarterly frequency using standard parameter values in the literature (Table 11). Ashenfelter, Farber, and Ransom (2010) survey the literature on the elasticity of labor supply firms face. They document that the short-run elasticity is in the 0.1-1.5 range, whereas the long-run elasticity is between 2 and 4. We take the middle of the range of these elasticities and set $\eta = 2$. The elasticity of demand θ is often calibrated at 10 in macroeconomic studies. However, because firms in our model compete not only with firms in the same sector, but also with firms in other sectors, we calibrate $\theta = 7$, which captures the notion that the elasticity of substitution across sectors is likely to be low. Other preference parameters are standard: $\sigma = 2$ and $\beta = 0.99$. Parameters of

[36] The fixed probability of price adjustment should be interpreted as a metaphor that allows particularly fast *non-linear* solutions to multi-sector models with large state spaces as well as easy interpretation of results. We find similar results in the Dotsey et al. (1999) model with state-dependent price adjustment.

the policy reaction function are taken from Taylor (1993) and Coibion and Gorodnichenko (2012). We follow Carvalho (2006) and calibrate the density function $f(k) = 1/5$ and use the empirical distribution of frequencies of price adjustment reported in Nakamura and Steinsson (2008) to calibrate $\{\lambda_k\}_{k=1}^{5}$. Specifically, we sort industries by the degree of price stickiness and construct five synthetic sectors that correspond to the quintiles of price stickiness observed in the data. Each sector covers a fifth of consumer spending. The Calvo rates of price adjustment range from 0.094 to 0.975 per quarter, with the median sector having a Calvo rate of 0.277 (which implies that this sector updates prices approximately once a year).

We solve the model using a third-order approximation as implemented in DYNARE, and simulate the model for 100 firms per sector for 2,000 periods, but discard the first 1,850 periods as burn-in. We then calculate for each firm and each time period the value of the firm $V(P_{jkt})$ and the value of the firm net of dividend $\tilde{V}(P_{jkt}) \equiv V(P_{jkt}) - (P_{jkt}Y_{jkt+s} - W_{jkt+s}N_{jkt+s})$, as well as the implied return $R_{jkt} = V(P_{jkt})/\tilde{V}(P_{jkt-1}) - 1$. Then we estimate the sensitivity of stock return volatility using the specification suggested previously:

$$R_{jkt}^2 = b_0 + b_1 \times v_t^2 + b_2 \times v_t^2 \times \lambda_j + b_3 \times \lambda_j + error. \tag{10}$$

We generate 2,000 histories and report average values of estimated b_1, b_2, and b_3 in Table 11 for the baseline calibration as well as for alternative parametrizations. We find that a large, positive $\hat{b}_1$ and a large, negative $\hat{b}_2$ are robust features of the model, with estimates in the ballpark of our empirical findings in Section IV. Magnitudes of the coefficients are such that $\hat{b}_1 + \hat{b}_2 \approx 0$. The estimates of $\hat{b}_3$ are negative, as predicted, but generally close to zero.

We can also use this model to calculate lost profits due to price stickiness: we compute the median profit $\bar{\pi}_k$ for each firm type k and then use $(\bar{\pi}_k - \bar{\pi}_5)/\bar{\pi}_5$ to assess how an increase in the duration of price spells from $(1/\lambda_5)$ (the sector with practically flexible prices) to $(1/\lambda_k)$ influences profits. We find that going from flexible prices to prices fixed for roughly one year (sector 3) reduces profits by about 25%. Although the only source of firm heterogeneity in the model is the duration of price spells, and thus differences in profits can be attributed to price stickiness, heterogeneous costs and benefits of price adjustment affect the duration of price spells in the data, such that the mapping of lost profits to the size of menu costs is likely to be complex. However, the magnitudes we observe in our simulations appear broadly in line with those observed in the data. For example, Zbaracki et al. (2004) show that a manufacturing firm with an average duration of price spells of one year spends about 20% of its net profit margin on nominal price adjustment.

Obviously, these calculations of menu-cost estimates depend on the model's structural parameters. One may use empirical moments to infer these structural parameters. The answer in this exercise is likely to depend on the details of the model, which can limit the robustness. However, these simulations highlight the relationship between price stickiness and returns, and provide a sense of magnitudes one might expect in a reasonably calibrated New Keynesian model with heterogeneous firms.

VI Concluding Remarks

Are sticky prices costly? We propose a simple framework to address this question, using the conditional volatility of stock market returns after monetary policy announcements. We document that the conditional volatility rises more for firms with stickier prices than for firms with more flexible prices. This differential reaction is economically and statistically large as well as strikingly robust to a broad spectrum of checks. This result suggests that menu costs—broadly defined to include physical costs of price adjustment, informational frictions, and so on—are an important factor for nominal price rigidity at the firm level. Our empirical evidence lends support to the New Keynesian interpretation of the observed nominal price rigidity at the microlevel: sticky prices are costly. Our results are qualitatively and, under plausible calibrations, quantitatively consistent with New Keynesian macroeconomic models in which firms have heterogeneous price stickiness. Our "model-free" evidence suggests sticky prices are indeed costly for firms, which is consistent with the tenets of New Keynesian macroeconomics.

Although our results do not prove that monetary shocks have real effects, they provide important building blocks for researchers and policymakers. First, our findings provide foundations for policy-workhorse macroeconomic models such as Christiano, Eichenbaum, and Evans (2005) in which nominal frictions play a prominent role. Second, increasing trend inflation—a policy that a number of economists suggest for combatting deflationary spirals in the Great Recession—has possibly non-negligible costs in light of our results.

Third, sticky prices are an important ingredient for generating large fiscal multipliers in theoretical models (especially in times of a binding zero lower bound on interest rates; see Christiano, Eichenbaum, and Rebelo (2011)). Finally, Bernanke and Kuttner (2005) emphasize that monetary policy can influence the economy via changes in asset prices, and our results can provide a new perspective on this channel, as well as highlight its distributional aspects.

The high-frequency identification of causal effects of monetary shocks on the volatility of stock returns suggests that connecting stock returns and measures of price stickiness is a fruitful avenue for future research. For example, Weber (2015) studies how firm-level and portfolio returns vary with measured price stickiness, which can provide a simple metric of the size of menu costs and shed new light on the sources of the cross-sectional distribution of returns. Alternatively, one may integrate asset prices into fully fledged DSGE models to obtain structural estimates of menu costs. We anticipate that using information on stock returns in conjunction with firm-level measures of price stickiness can help to discriminate between alternative models explaining the large real effect of monetary policy with moderate degrees of price stickiness and the inertial reaction of inflation, improve our understanding of how to price securities, and further bridge finance and macroeconomics.

References

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review 93*(1), 38–62.

Anderson, E., N. Jaimovich, and D. Simester (2012). Price stickiness: Empirical evidence of the menu cost channel. *Unpublished Manuscript, Northwestern University*.

Ashenfelter, O. C., H. Farber, and M. R. Ransom (2010). Labor market monopsony. *Journal of Labor Economics 28*(2), 203–210.

Barattieri, A., S. Basu, and P. Gottschalk (2014). Some evidence on the importance of sticky wages. *American Economic Journal: Macroeconomics 6*(1), 70–101.

Belsley, D., E. Kuh, and R. Welsch (1980). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York John Wiley and Sons.

Berger, D. and J. Vavra (2013). Dynamics of the U.S. price distribution. *Unpublished manuscript, University of Chicago*.

Bernanke, B. S. and K. N. Kuttner (2005). What explains the stock market's reaction to Federal Reserve policy? *The Journal of Finance 60*(3), 1221–1257.

Bhattarai, S. and R. Schoenle (2014). Multiproduct firms and price-setting: Theory and evidence from u.s. producer prices. *Journal of Monetary Economics 66*(0), 178–192.

Bils, M. and P. J. Klenow (2004). Some evidence on the importance of sticky prices. *Journal of Political Economy 112*(5), 947–985.

Bils, M., P. J. Klenow, and B. A. Malin (2012). Testing for Keynesian labor demand. In *NBER Macroeconomics Annual*, Volume 27, pp. 311–349.

Blinder, A. S. (1991). Why are prices sticky? Preliminary results from an interview study. *American Economic Review 81*(2), 89–96.

Bollen, K. A. and R. W. Jackman (1990). Regression diagnostics: An expository treatment of outliers and influential cases. In *Modern Methods of Data Analysis*, pp. 257–291. Newbury Park, CA: Sage.

Bomfim, A. N. (2003). Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. *Journal of Banking & Finance 27*(1), 133–151.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics 12*(3), 383–398.

Campbell, J. Y. (1991). A variance decomposition for stock returns. *The Economic Journal 101*(405), 157–179.

Carvalho, C. (2006). Heterogeneity in price stickiness and the real effects of monetary shocks. *The B.E. Journal of Macroeconomics 2*(1), 1.

Christiano, L., M. Eichenbaum, and S. Rebelo (2011). When is the government spending multiplier large? *Journal of Political Economy 119*(1), 78 – 121.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy 113*(1), 1–45.

Cochrane, J. H. (1992). Explaining the variance of price-dividend ratios. *Review of Financial Studies 5*(2), 243–280.

Coibion, O. and Y. Gorodnichenko (2012). Why are target interest rate changes so persistent? *American Economic Journal: Macroeconomics 4*(4), 126–162.

Coibion, O., Y. Gorodnichenko, and J. Wieland (2012). The optimal inflation rate in new keynesian models: Should central banks raise their inflation targets in light of the zero lower bound? *Review of Economic Studies 79*(4), 1371–1406.

Cook, T. and T. Hahn (1989). The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics 24*(3), 331 – 351.

Dotsey, M., R. G. King, and A. L. Wolman (1999). State-dependent pricing and the general equilibrium dynamics of money and output. *The Quarterly Journal of Economics 114*(2), 655–690.

Driscoll, J. C. and A. C. Kraay (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics 80*(4), 549–560.

Ehrmann, M. and M. Fratzscher (2004). Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit, and Banking 36*(4), 719–737.

Eichenbaum, M., N. Jaimovich, S. Rebelo, and J. Smith (2014). How frequent are small price changes? *American Economic Journal: Macroeconomics 6*(2), 137–155.

Eichenbaum, M., N. Jaimovich, and S. T. Rebelo (2011). Reference prices, costs, and nominal rigidities. *American Economic Review 101*(1), 234–262.

Erenburg, G., A. Kurov, and D. J. Lasser (2006). Trading around macroeconomic announcements: Are all traders created equal? *Journal of Financial Intermediation 15*(4), 470 – 493.

Faust, J., E. T. Swanson, and J. H. Wright (2004a). Do Federal reserve policy surprises reveal superior information about the economy? *Contributions to Macroeconomics 4*(1), 1–29.

Faust, J., E. T. Swanson, and J. H. Wright (2004b). Identifying VARs based on high frequency futures data. *Journal of Monetary Economics 51*(6), 1107–1131.

Goldberg, P. P. and R. Hellerstein (2011). How rigid are producer prices? *FRB of New York Staff Report*, 1–55.

Gomes, J., L. Kogan, and M. Yogo (2009). Durability of output and expected stock retums. *Journal of Political Economy 117*(5), 941–986.

Green, T. C. (2004). Economic news and the impact of trading on bond prices. *The Journal of Finance 59*(3), 1201–1234.

Gürkaynak, R. S., B. P. Sack, and E. T. Swanson (2005). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking 1*(1), 55–94.

Gürkaynak, R. S. and J. Wright (2013). Identification and inference using event studies. Technical report, CEPR Discussion Papers.

Haltiwanger, J. and M. Waldman (1991). Responders versus non-responders: A new perspective on heterogeneity. *Economic Journal 101*(408), 1085–1102.

Harris, M. and A. Raviv (1993). Differences of opinion make a horse race. *Review of Financial Studies 6*(3), 473–506.

Head, A., L. Q. Liu, G. Menzio, and R. Wright (2012). Sticky prices: A new monetarist approach. *Journal of the European Economic Association 10*(5), 939–973.

Ippolito, F., A. K. Ozdagli, and A. Perez (2013). Is bank debt special for the transmission of monetary policy? Evidence from the stock market. *Unpublished manuscript, Universitat Pompeu Fabra*.

Jensen, G. R., J. M. Mercer, and R. R. Johnson (1996). Business conditions, monetary policy, and expected security returns. *Journal of Financial Economics 40*(2), 213–237.

Klenow, P. J. and B. A. Malin (2010). Chapter 6 - Microeconomic Evidence on Price-Setting. Volume 3 of *Handbook of Monetary Economics*, pp. 231 – 284. Elsevier.

Klenow, P. J. and J. L. Willis (2007). Sticky information and sticky prices. *Journal of Monetary Economics 54, Supplement*, 79–99.

Midrigan, V. (2011). Menu costs, multiproduct firms, and aggregate fluctuations. *Econometrica 79*(4), 1139–1180.

Nakamura, E. and J. Steinsson (2008). Five facts about prices: A reevaluation of menu cost models. *Quarterly Journal of Economics 123*(4), 1415–1464.

Nakamura, E. and J. Steinsson (2013). Price rigidity: Microeconomic evidence and macroeconomic implications. *Annual Review of Economics 5*(1), 133–163.

Neuhierl, A., A. Scherbina, and B. Schlusche (2013). Market reaction to corporate press releases. *Journal of Financial and Quantitative Analysis 48*(04), 1207–1240.

Oster, E. (2013). Unobservable selection and coefficient stability: Theory and validation.

Piazzesi, M. (2005). Bond yields and the Federal Reserve. *Journal of Political Economy 113*(2), 311–344.

Piazzesi, M. and E. T. Swanson (2008). Futures prices as risk-adjusted forecasts of monetary policy. *Journal of Monetary Economics 55*(4), 677–691.

Rigobon, R. and B. P. Sack (2003). Measuring the reaction of monetary policy to the stock market. *Quarterly Journal of Economics 118*(2), 639–669.

Rigobon, R. and B. P. Sack (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics 51*(8), 1553–1575.

Romer, D. H. and C. D. Romer (2000, June). Federal reserve information and the behavior of interest rates. *American Economic Review 90*(3), 429–457.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy 39*(1), 195–214.

Varian, H. R. (1989). Differences of opinion in financial markets. *Financial Risk: Theory, Evidence and Implications*, 3–37.

Vavra, J. (2014). Inflation dynamics and time-varying volatility: New evidence and an Ss interpretation. *The Quarterly Journal of Economics 129*(1), 215–258.

Vuolteenaho, T. (2002). What drives firm-level stock returns? *The Journal of Finance 57*(1), 233–264.

Weber, M. (2015). Nominal rigidities and asset pricing. *Unpublished manuscript, University of Chicago Booth School of Business*.

Zbaracki, M. J., M. Ritson, D. Levy, S. Dutta, and M. Bergen (2004). Managerial and customer costs of price adjustment: Direct evidence from industrial markets. *The Review of Economics and Statistics 86*(2), 514–533.

Zebedee, A. A., E. Bentzen, P. R. Hansen, and A. Lunde (2008). The Greenspan years: an analysis of the magnitude and speed of the equity market response to FOMC announcements. *Financial Markets and Portfolio Management 22*(1), 3–20.

Table 1: **Frequency of Price Adjustment by Industry**

This table reports average frequencies of price adjustments (Panel A), synchronization of price adjustment within firm (Panel B), the number of products in the producer price index micro data per firm (Panel C), and the number of price spells per firm (Panel D). We define synchronization of price adjustment as the share of price quotes of a given firm in a given month that have a price change. For example, if a firm in a given month has five products in the BLS sample and two of the products have a price change, the synchronization rate is 2/5. Standard deviations are in parentheses, and number of observations are reported at the bottom of the table. Equally-weighted statistics are calculated at the firm level using the microdata underlying the producer price index.

Panel A. Frequency of Price Adjustment							
	Total	Agriculture	Manufacturing	Utilities	Trade	Finance	Service
Mean	14.17%	26.96%	11.57%	19.12%	19.70%	13.14%	8.47%
Std	(13.08%)	(17.91%)	(11.19%)	(13.93%)	(13.50%)	(11.63%)	(8.85%)
Panel B. Synchronization of Price Adjustment							
	Total	Agriculture	Manufacturing	Utilities	Trade	Finance	Service
Mean	14.45%	26.33%	11.60%	20.46%	16.99%	14.03%	9.77%
Std	(10.81%)	(17.34%)	(8.54%)	(11.04%)	(9.24%)	(9.42%)	(7.42%)
Panel C. Number of Products							
	Total	Agriculture	Manufacturing	Utilities	Trade	Finance	Service
Mean	110.59	93.67	113.64	199.34	82.99	72.50	69.25
Median	64.18	40.54	73.64	181.51	42.17	44.96	31.99
Std	(124.54)	(112.81)	(119.56)	(177.70)	(96.78)	(74.72)	(82.10)
Panel D. Number of Price Spells							
	Total	Agriculture	Manufacturing	Utilities	Trade	Finance	Service
Mean	202.91	175.39	171.55	485.96	174.60	138.87	87.85
Std	(349.23)	(212.53)	(316.93)	(565.01)	(190.31)	(244.57)	(128.18)
Nobs	760	52	342	109	45	138	74

Table 2: **Descriptive Statistics For High-Frequency Data**

This table reports descriptive statistics for monetary policy shocks (bps) in Panel A and for the returns of the S&P500 in Panel B separately for all 137 event days between 1994 and 2009, turning points in monetary policy, and intermeeting policy decisions. The policy shock is calculated according to equation (2) as the scaled change in the current month federal funds futures in a 30 minutes (tight) window bracketing the FOMC press releases and a 60 minutes (wide) event window around the release times, respectively. The return of the S&P500 is calculated as weighted average of the constituents' returns in the respective event windows, where the market capitalizations at the end of the previous trading days are used to calculate the weights.

	All Event Days		Turning Points		Intermeeting Releases	
	Tight	Wide	Tight	Wide	Tight	Wide
Panel A. Monetary Policy Shocks						
Mean	−1.60	−1.46	−6.09	−5.68	−12.23	−11.09
Median	0.00	0.00	−1.75	−2.75	−5.73	−5.15
Std	8.94	9.11	17.28	16.40	23.84	25.23
Min	−46.67	−46.30	−39.30	−36.50	−46.67	−46.30
Max	16.30	15.20	16.30	15.20	15.00	15.00
Correlation	0.99		0.99		0.99	
Nobs	137		8		8	
Panel B. S&P500 Returns						
Mean	−0.05%	0.05%	0.71%	0.71%	−0.04%	−0.06%
Median	−0.12%	0.02%	0.30%	0.50%	0.64%	0.42%
Std	0.91%	0.97%	1.73%	1.52%	2.83%	2.90%
Min	−5.12%	−5.12%	−0.81%	−0.78%	−5.12%	−5.12%
Max	4.32%	3.61%	4.32%	3.61%	2.69%	2.69%
Correlation	0.90		0.99		0.99	
Nobs	137		8		8	

Table 3: **Response of the S&P500 to Monetary Policy Shocks**

This table reports the results of regressing returns and squared returns in percent of the S&P500 in an event window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shocks calculated according to equation (2), v_t, and the squared shocks, v_t^2, for different event types in a 30 minutes window bracketing the FOMC press releases. The return of the S&P500 is calculated as a weighted average of the constituents' return in the respective event window, where the market capitilization at the end of the previous trading day is used to calculate the weights. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Newey-West standard errors are reported in parentheses.

	Returns		Squared Returns			
	All	pre-2005	All	Regular	Turning Point	Intermeeting
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.08	−0.12*	0.13	0.23***	−0.36	2.68
	(0.06)	(0.05)	(0.13)	(0.05)	(0.77)	(1.64)
v_t	−1.66	−5.31***				
	(2.93)	(1.41)				
v_t^2			84.38***	9.57	116.60***	67.15
			(23.18)	(8.67)	(9.68)	(38.79)
R^2	0.03	0.44	0.69	0.02	0.92	0.53
Observations	137	92	137	121	8	8

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4: **Response of the Constituents of the S&P500 to Monetary Policy Shocks**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in different event windows bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shocks calculated according to equation (2), v_t^2, the frequency of price adjustment, FPA, as well as their interactions. See specification (3). Equally-weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses. See text for further details.

Panel A. Baseline

	Tight Window		Firm FE		Firm & Event FE		Wide Window		Daily Window	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2	128.50***	76.95***	127.50***	77.00***			119.60***	95.38***	245.60**	158.4**
	(29.50)	(15.95)	(29.45)	(15.78)			(38.89)	(24.82)	(119.50)	(73.77)
$FPA \times v_t^2$	−169.80**	−67.26***	−168.00**	−67.82***	−166.60**	−43.96***	−130.40*	−78.08***	−340.10	−178.30
	(82.32)	(5.02)	(80.35)	(4.47)	(81.32)	(5.21)	(77.88)	(27.10)	(233.10)	(123.60)
FPA	0.41	0.09					0.55	0.08	0.11	−2.26
	(0.33)	(0.16)					(0.59)	(0.21)	(2.68)	(2.29)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.12	0.12	0.14	0.15	0.20	0.26	0.03	0.09	0.01	0.00
Observations	57,541	57,441	57,541	57,441	57,541	57,422	57,541	55,022	57,541	57,506

Panel B. Variations

	Volume Weighted		Absolute Returns & Shocks		Market adj		CAPM adj		Fama & French adj	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2 (or $\|v_t\|$)	144.50***	86.42***	6.33***	5.37***	47.76**	25.40***	43.80***	27.71***	38.29***	25.80***
	(43.96)	(16.24)	(1.17)	(1.03)	(18.91)	(8.13)	(11.39)	(6.84)	(7.76)	(4.63)
$FPA \times v_t^2$ $(or \|v_t\|)$	−205.90*	−64.59***	−4.11**	−2.84***	−71.52**	−13.20***	−52.96***	−18.35***	−42.57**	−22.52***
	(119.30)	(22.71)	(1.97)	(0.88)	(32.33)	(1.88)	(18.46)	(5.99)	(20.11)	(4.38)
FPA	0.82	0.45	0.11	0.06*	0.05	−0.12	−0.12	−0.23	−0.24	−0.25
	(0.63)	(0.50)	(0.07)	(0.03)	(0.20)	(0.18)	(0.20)	(0.19)	(0.22)	(0.21)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.06	0.04	0.21	0.19	0.03	0.03	0.03	0.03	0.02	0.02
Observations	55,065	54,996	57,541	57,426	57,541	57,492	57,541	57,491	57,541	57,497

Panel C. Condition on Event Type

	baseline		pre 2007		change in FFR		| shock | > 0.05		turning point	intermeeting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2	128.50***	76.95***	123.10***	53.81***	133.50***	83.76***	134.50***	90.13***	235.10***	78.25***
	(29.50)	(15.95)	(48.87)	(4.61)	(30.86)	(16.90)	(32.44)	(19.49)	(17.32)	(32.00)
$FPA \times v_t^2$	−169.80**	−67.26***	−245.80***	−77.75***	−178.10**	−64.97***	−185.60**	−77.20***	−512.20***	−99.31**
	(82.32)	(5.02)	(111.50)	(12.44)	(86.90)	(9.42)	(91.46)	(19.98)	(42.76)	(37.64)
FPA	0.41	0.09	0.54*	0.02	1.01*	0.48	2.23	0.90	5.48*	1.66
	(0.33)	(0.16)	(0.39)	(0.09)	(0.64)	(0.35)	(1.43)	(0.76)	(2.98)	(4.81)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes	No/Yes	No/Yes
R^2	0.12	0.12	0.11	0.13	0.14	0.13	0.12	0.16	0.15	0.04
Observations	57,541	57,441	45,891	45,775	24,752	24,676	15,580	15,525	3,407	3,300

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 5: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (firm & industry level controls)**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2, the frequency of price adjustment, FPA, as well as their interactions. See specification (3). Equally-weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. pcm is the price cost margin defined as sales minus cost of goods sold over sales, $4F - conc\ ratio$ is the four-firm concentration ratio, bm is the book-to-market ratio, and size is the logarithm of the market capitalization. std sale is the volatility of annual sales growth at the quarterly frequency, nondur, serv, invest, gov and nx follow the durable goods classification of Gomes et al. (2009), dura is the durability measure of Bils et al. (2012), labor share is the share of total staff expenses in sales, FWA is the frequency of wage adjustment of Barattieri et al. (2014), RecPay2Y is receivables minus payables to sales, I2Y is investment to sales and D2A is depreciation and amortization over total assets. engel are the Engel curve slopes of Bils et al. (2012), sync is the degree of synchronization in price adjustment at the firm level, #prod is the number of products in the producer price data, Rat is the S&P long term issuer rating, KZ is the Kaplan-Zingales index, Lev is financial leverage, FC2Y is fixed costs to sales, and export is fraction of foreign sales in total sales. The full sample ranges from February 1994 through December 2009, excluding the release of September 17th 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
v_t^2	77.00***	53.14***	82.75***	38.93	−181.30***	49.16***	80.78***	71.05***	127.10***	115.70***
	(15.78)	(18.21)	(16.95)	(33.69)	(36.06)	(11.73)	(11.23)	(17.71)	(24.47)	(23.59)
$FPA \times v_t^2$	−67.82***	−45.52***	−67.68***	−65.03***	−63.02***	−74.70***	−54.57***	−59.91***	−96.51***	−76.12***
	(4.47)	(7.57)	(7.51)	(4.89)	(5.59)	(7.52)	(11.41)	(8.52)	(32.40)	(10.92)
$v_t^2 \times pcm$		52.18***								
		(19.60)								
$v_t^2 \times 4F - conc\ ratio$			−43.22***							
			(10.97)							
$v_t^2 \times bm$				−2.60						
				(1.90)						
$v_t^2 \times size$					16.04***					
					(2.94)					
$v_t^2 \times std\ sale$						532.50***				
						(75.86)				
$v_t^2 \times nondur$							−33.96***			
							(5.29)			
$v_t^2 \times serv$							−27.78***			
							(3.83)			
$v_t^2 \times invest$							7.34			
							(8.97)			
$v_t^2 \times gov$							29.69***			
							(6.34)			
$v_t^2 \times nx$							−0.93			
							(9.77)			
$v_t^2 \times dura$								11.60***		
								(2.07)		
$v_t^2 \times labor\ share$									−91.70**	
									(45.98)	
$v_t^2 \times FWA$										−255.80
										(203.30)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15	0.17	0.15	0.15	0.16	0.17	0.25	0.16	0.15	0.20
Observations	57,441	51,929	50,126	57,441	57,443	51,929	42,990	47,422	9,722	47,388

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

continued on next page

Table 5: **Continued from Previous Page**

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
v_t^2	76.87***	75.71***	85.62***	19.01	92.35***	85.23***	144.70***	71.74***	102.10***	45.29*	71.51***	−128.60
	(15.75)	(13.58)	(17.68)	(24.45)	(16.59)	(16.07)	(19.29)	(16.92)	(18.05)	(23.47)	(19.60)	(115.00)
$FPA \times v_t^2$	−74.10***	−61.80***	−63.52***	−24.76***	−52.22***	−35.33***	−63.20***	−73.44***	−56.14***	−23.50***	−40.36***	−188.70***
	(6.28)	(5.36)	(4.99)	(5.01)	(4.57)	(12.80)	(7.31)	(7.39)	(10.10)	(3.83)	(9.85)	(38.84)
$v_t^2 \times pcm$												−160.30**
												(76.24)
$v_t^2 \times 4F - conc\ ratio$												−62.34**
												(26.21)
$v_t^2 \times bm$												0.01
												(1.61)
$v_t^2 \times size$												33.51***
												(6.18)
$v_t^2 \times std\ sale_a$												1,084.00**
												(442.50)
$v_t^2 \times nondur$												−39.94**
												(18.94)
$v_t^2 \times serv$												15.08
												(12.13)
$v_t^2 \times invest$												−14.30**
												(6.31)
$v_t^2 \times gov$												45.58**
												(22.20)
$v_t^2 \times nx$												71.53***
												(6.55)
$v_t^2 \times dura$												14.78***
												(4.09)
$v_t^2 \times labor\ share$												
$v_t^2 \times FWA$												−1,813.00***
												(380.10)
$v_t^2 \times RecPay2Y$	−1.72											−30.39
	(1.12)											(38.59)
$v_t^2 \times I2Y$		−15.00										−7.17
		(37.91)										(125.50)
$v_t^2 \times D2A$			−260.30**									191.30
			(130.90)									(195.90)
$v_t^2 \times engel$				57.18***								−32.49*
				(12.87)								(19.12)
$v_t^2 \times sync$					−49.40							51.98
					(39.35)							(73.44)
$v_t^2 \times \#prod$						−0.10***						−0.05***
						(0.02)						(0.02)
$v_t^2 \times Rat$							−20.89***					−12.91***
							(3.02)					(4.23)
$v_t^2 \times KZ$								5.50*				17.00***
								(3.19)				(2.85)
$v_t^2 \times Lev$									−57.41***			−54.35**
									(8.25)			(22.89)
$v_t^2 \times FC2Y$										141.50**		174.50
										(57.74)		(119.30)
$v_t^2 \times export$											0.18	0.00
											(0.26)	(0.26)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15	0.11	0.11	0.160	0.13	0.16	0.17	0.15	0.16	0.17	0.26	0.36
Observations	55,884	55,566	56,146	47,415	57,319	57,433	53,284	56,351	56,388	56,474	31,689	19,796

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (within industry)**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2 *and the interaction term with the frequency of price adjustment, FPA. Columns (10) and (11) exclude durable goods producers. See specification (3). Equally-weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses.*

	All		Agro	Mnfg	Util	Trade	Finance	Service		excl. Durables	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
v_t^2	127.50***	77.00***	81.73*	71.85***	73.68***	74.38***	86.48***	61.28***	80.15***	106.70***	63.95***
	(29.45)	(15.78)	(45.16)	(12.80)	(20.23)	(17.95)	(20.56)	(13.66)	(15.69)	(18.87)	(15.91)
$FPA \times v_t^2$	−168.00**	−67.82***	−106.60*	−35.99**	−125.00***	−54.99	−20.11	168.60***	33.97	−112.90**	−29.45***
	(80.35)	(4.47)	(59.35)	(14.35)	(16.73)	(35.34)	(23.41)	(51.38)	(71.08)	(48.95)	(5.12)
Correction for outliers	No	Yes	No	No	No	No	No	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
R^2	0.14	0.15	0.18	0.22	0.21	0.25	0.09	0.21	0.18	0.12	0.12
Observations	57,541	57,441	3,629	27,887	7,394	3,839	9,836	4,856	4,815	31,805	31,736

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 7: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (controlling for return sensitivity to monetary policy surprises)**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2 *the frequency of price adjustment, FPA, as well as their interactions controlling for the sensitivity of returns to monetary policy shocks,* β_{v_t}*. See specification (3). Equally-weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses.*

	baseline		sq return sens		return sens		abs return sens	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
v_t^2	128.50***	76.95***	93.83***	62.03***	117.10***	70.63***	71.95***	49.89 **
	(29.50)	(15.95)	(22.95)	(19.34)	(27.13)	(19.92)	(26.06)	(23.08)
$FPA \times v_t^2$	−169.80 **	−67.26***	−157.90 **	−62.11***	−160.80 **	−61.02***	−170.70 **	−62.17***
	(82.32)	(5.02)	(72.97)	(10.12)	(69.99)	(5.52)	(81.12)	(7.31)
FPA	0.41	0.09	0.81*	0.28	0.47	0.01	0.61	0.16
	(0.33)	(0.16)	(0.45)	(0.18)	(0.38)	(0.15)	(0.39)	(0.17)
$\beta_{v_t}^2 \times v_t^2$			5.54*	2.71***				
			(2.82)	(0.98)				
$\beta_{v_t} \times v_t^2$					−13.52	−6.42		
					(18.05)	(6.82)		
$\|\beta_{v_t}\| \times v_t^2$							35.20*	17.21 **
							(18.45)	(6.97)
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.12	0.12	0.15	0.14	0.12	0.09	0.14	0.13
Observations	57,541	57,441	57,541	57,433	57,541	57,436	57,541	57,429

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 8: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (non-linear effects of FPA)**

This table reports the results of regressing squared percentage returns of the constituents of the S&P500 in event windows bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shocks calculated according to equation (2), v_t^2, the frequency of price adjustment, FPA, as well as their interactions for different parts of the distribution of FPA. FPA50 denotes the median of the FPA distribution. Columns (1)-(4) are for specification (3). Columns (5) and (6) estimate a quadratic specification (see specification (4)). Columns (5)-(9) are for specification (5). Equally-weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses.

	FPA < FPA50		FPA >= FPA50		quadratic specification		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
v_t^2	161.00***	98.52***	115.30***	84.60***	140.90***	81.67***	145.60***	112.70***	100.90***	93.47***	70.67***
	(53.46)	(14.15)	(25.29)	(17.17)	(35.52)	(15.87)	(42.42)	(30.73)	(22.58)	(25.46)	(18.75)
$FPA \times v_t^2$	−929.00	−524.00***	−117.20***	−93.39***	−392.50	−125.60***					
	(873.60)	(65.27)	(25.64)	(11.04)	(266.00)	(29.00)					
$FPA^2 \times v_t^2$					524.80	121.50					
					(437.80)	(97.41)					
FPA	−1.40	−1.78	0.29	0.00	0.19	−0.15					
	(3.25)	(1.15)	(0.28)	(0.13)	(1.03)	(0.37)					
FPA^2					0.55	0.92					
					(2.00)	(0.96)					
Correction outlier	No	Yes	No	Yes	No	Yes	No	No	No	No	No
R^2	0.11	0.07	0.14	0.13	0.12	0.11	0.09	0.13	0.21	0.15	0.10
Observations	27,222	27,117	30,319	30,192	57,541	57,403	10,098	11,783	11,342	12,729	11,589

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 9: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (relative and pseudo event volatilities)**

This table reports the results of regressing the ratio of squared percentage returns of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases over the squared percentage returns in a pseudo event window between adjacent event dates on the federal funds futures based measure of monetary policy surprises calculated according to equation (2), v_t^2 *and the interaction term with the frequency of price adjustment, FPA in Panel A. Panel B regresses squared percentage returns of the constituents of the S&P500 in a 30 minutes pseudo event window between adjacent event dates on the federal funds futures based measure of monetary policy surprises calculated according to equation (2),* v_t^2 *and the interaction term with the frequency of price adjustment, FPA. See specification (3). Equally-weighted frequencies of price adjustments are calculated at the firm level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses.*

Panel A. Relative Volatilities

	Tight Window		Firm FE		Event FE		Firm & Event FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
v_t^2	0.57***	0.32***	0.57***	0.33***				
	(0.08)	(0.05)	(0.07)	(0.05)				
$FPA \times v_t^2$	−1.07***	−0.65***	−1.05***	−0.64***	−1.06***	−0.57***	−1.05***	−0.56***
	(0.19)	(0.17)	(0.17)	(0.17)	(0.19)	(0.18)	(0.18)	(0.18)
FPA	0.00***	0.00***			0.00***	0.00***		
	(0.00)	(0.00)			(0.00)	(0.00)		
Event Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.07	0.02	0.09	0.05	0.12	0.10	0.14	0.12
Observations	53,682	53,547	53,682	53,547	53,682	53,507	53,682	53,507

Panel B. Pseudo Event Volatilities

	Tight Window		Firm FE		Event FE		Firm & Event FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
v_t^2	2.26	2.01	2.33	2.04				
	(3.79)	(3.33)	(3.57)	(3.07)				
$FPA \times v_t^2$	5.68	−2.05	5.25	−2.11	5.96	−2.19	5.51	−2.33
	(7.60)	(4.78)	(6.91)	(3.88)	(7.60)	(4.66)	(6.92)	(3.80)
FPA	−0.17***	−0.15***			−0.17***	−0.15***		
	(0.04)	(0.04)			(0.04)	(0.04)		
Event Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Correction for outliers	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.00	0.00	0.06	0.06	0.06	0.07	0.11	0.12
Observations	53,262	53,248	53,262	53,248	53,262	53,247	53,262	53,247

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 10: **Response of the Constituents of the S&P500 to Monetary Policy Shocks (profitability and capex)**

This table reports the results of regressing squared percentage changes in mean quarterly operating income before depreciation (Panel A) and capital expenditure (Panel B) between quarters $t+H$ till $t+H+3$ and $t-4$ till $t-1$ normalized by $t-1$ total assets of the constituents of the S&P500 in a 30 minutes window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy surprises calculated according to equation (2) and accumulated to quarterly frequency, $\tilde{v}_t^2$, the frequency of price adjustment, FPA, as well as their interaction. See specification (7). Equally-weighted frequencies of price adjustments are calculated at the establishment level using the microdata underlying the producer price index. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations. Standard errors are clustered at the event level and reported in parentheses.

Panel A. Profitability

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5	H = 6	H = 7	H = 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\tilde{v}_t^2$	2.47*	1.75	−0.03	−2.10	−3.69	−7.98 **	−10.51*	−15.99***	−21.55***
	(1.35)	(1.65)	(1.85)	(2.07)	(2.75)	(3.49)	(5.10)	(5.43)	(6.43)
$FPA \times \tilde{v}_t^2$	−19.68***	−23.98***	−25.62***	−30.91 **	−36.81 **	−35.18 **	−41.58 **	−29.98	−29.68
	(4.87)	(6.88)	(7.01)	(8.90)	(12.59)	(13.34)	(17.65)	(20.69)	(23.82)
FPA	2.10***	2.68***	3.24***	3.78***	4.07***	4.01 **	4.77 **	4.70*	4.88
	(0.26)	(0.39)	(0.56)	(0.73)	(0.87)	(1.00)	(1.39)	(1.58)	(1.91)
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	20,756	20,428	20,117	19,814	19,646	19,449	19,295	18,921	18,475

Panel B. Capex

	H = 0	H = 1	H = 2	H = 3	H = 4	H = 5	H = 6	H = 7	H = 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\tilde{v}_t^2$	0.35	0.40	0.73	0.99	0.97	1.41	1.74	2.03	1.56
	(0.53)	(0.82)	(1.00)	(1.20)	(1.27)	(1.48)	(1.81)	(2.14)	(2.29)
$FPA \times \tilde{v}_t^2$	−4.64*	−4.84	−10.06 **	−17.56***	−22.14***	−28.55***	−33.48***	−36.15***	−41.64***
	(2.72)	(3.67)	(4.47)	(4.04)	(4.34)	(4.18)	(3.56)	(5.03)	(6.41)
FPA	1.93***	2.66***	3.29***	3.95***	4.38***	4.73***	5.19***	6.03***	6.96***
	(0.22)	(0.31)	(0.43)	(0.51)	(0.55)	(0.49)	(0.46)	(0.46)	(0.56)
Correction for outlier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Observations	23,192	22,982	22,788	22,599	22,414	22,233	22,053	21,879	21,714

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 11: **Multi-sector model**

This table shows in Panel A calibrated parameter values for the dynamic New Keynesian multisector model described in Section V, the sectoral distribution of the frequency of price adjustment in Panel B, and the parameter estimates of equation (10) with simulated data from the model in Panel C.

Panel A. Calibration

Parameter	Value	Source
η	2	Ashenfelter et al. (2010)
σ	2	standard
θ	7	standard
β	0.99	standard
ϕ_π	1.5	Taylor (1993)
ϕ_y	0.5	Taylor (1993)
ρ_{mp}	0.9	Coibion and Gorodnichenko (2012)
$std(v_t)$	0.0043	Coibion et al. (2012)

Panel B. Sectoral Distribution

Sector k	Share	Frequency of Price Adjustment
1	0.2	0.094
2	0.2	0.164
3	0.2	0.277
4	0.2	0.638
5	0.2	0.985

Panel C. Simulation Results

Calibration	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$
baseline	221.5	-256.0	-0.008
$\sigma = 3$	161.2	-177.5	-0.006
$\eta = 1$	433.5	-513.8	-0.014
$\theta = 6$	114.0	-120.7	-0.004
$\phi_\pi = 2$	108.0	-127.5	-0.004
$\phi_y = 0.75$	245.7	-287.9	-0.009
$\rho_{mp} = 0.91$	410.5	-494.7	-0.015
$std(v_t) = 0.004$	197.7	-226.2	-0.006